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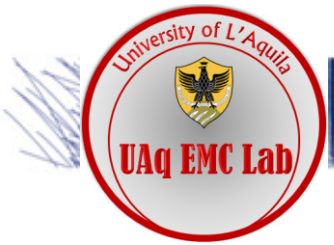

FACULTY OF ENGINEERING

August 5–10, 2012
Pittsburgh, Pennsylvania
2012 IEEE Symposium on Electromagnetic Compatibility
www.emc2012.isemc.org

Tutorial: Advanced Topics in Signal and Power Integrity

Parameterized Models for Efficient Design in EMC and SI Applications

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** Dipartimento di Ingegneria Elettrica e dell'Informazione, Università degli Studi dell'Aquila

† CST of America

Outline

Introduction

Parameterized Macromodels

Numerical examples

- **EMC example**
- **SI example**

Conclusions

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EMC 2012 PITTSBURGH, PA

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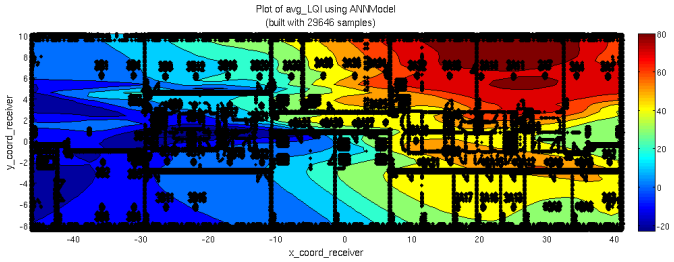
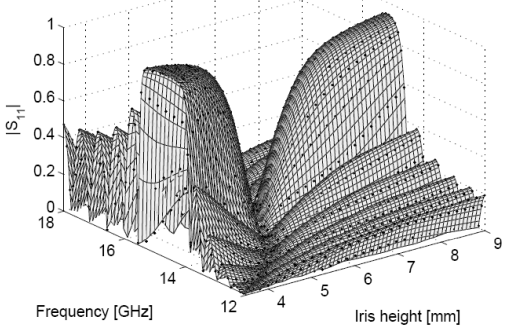
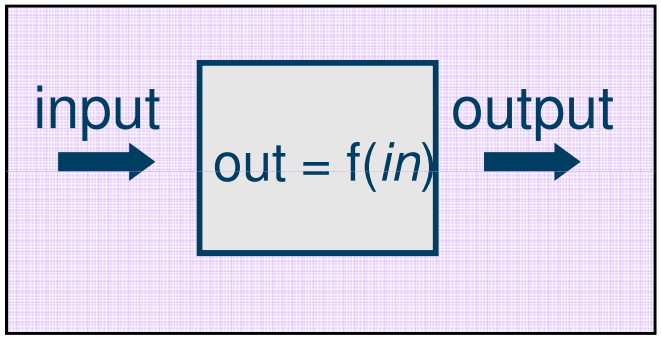


electronics





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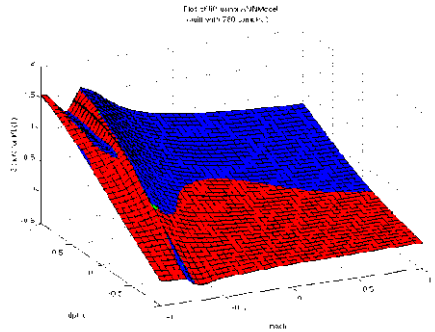
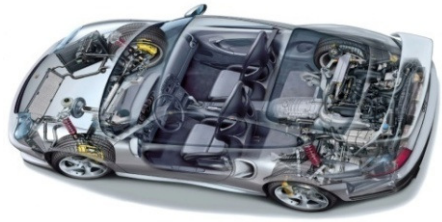


automotive



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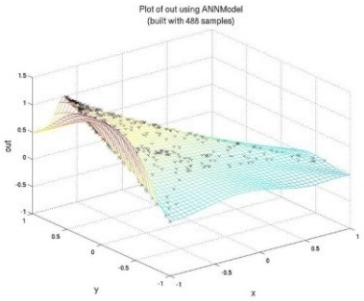
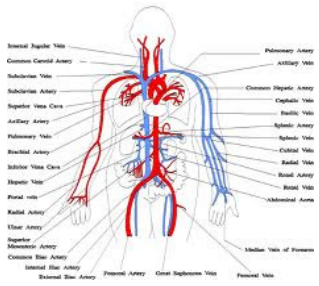


biomodeling



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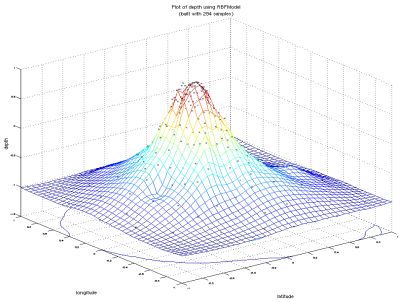
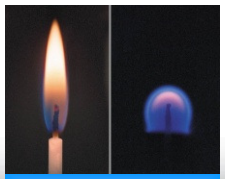
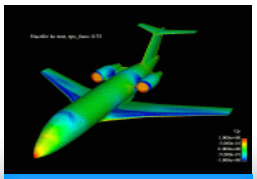
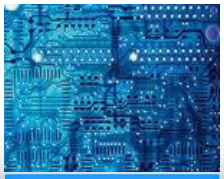



Automotive | Chemistry | Aerodynamics | Electronics | Metallurgy

Design variables

width, temperature, angle, frequency, ...

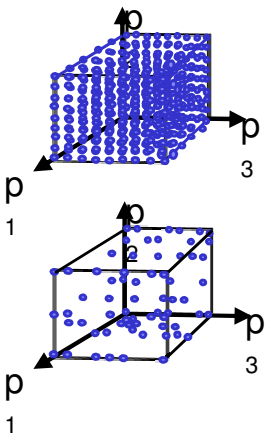
Simulation Model

Fluent®, HSPICE®, CST®, Comsol®, Abaqus®, ...

Costly

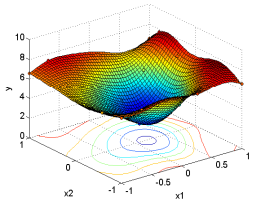
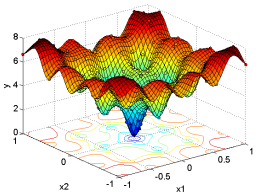
Response variables

lift, S-parameters, pressure, stress, ...



Configurable infrastructure

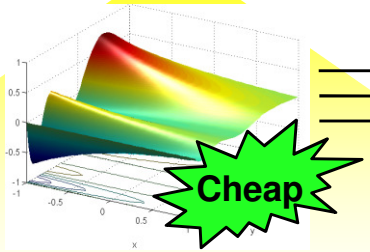
Adaptive Modeling

Distributed Computing

Design variables

Response variables

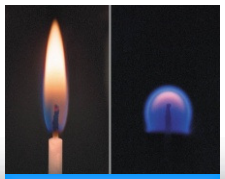
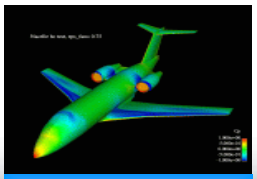
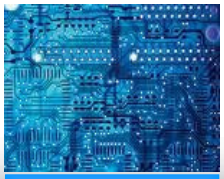


Cheap

Parameterized Macromodel

Neural network, Kriging, SVM, rational function, spline,...

Prototyping | Optimization | Sensitivity Analysis | CAD/CAM/CAE Environment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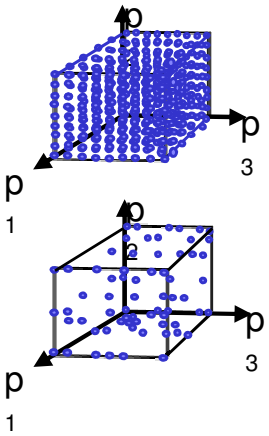

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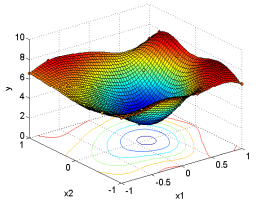
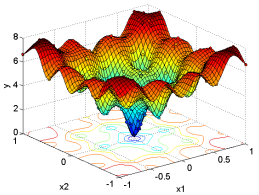

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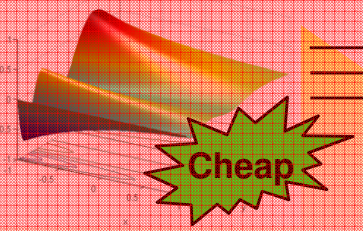

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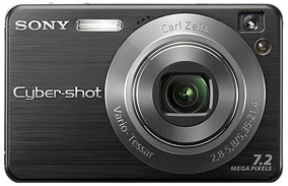
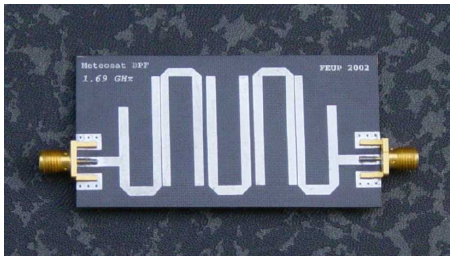
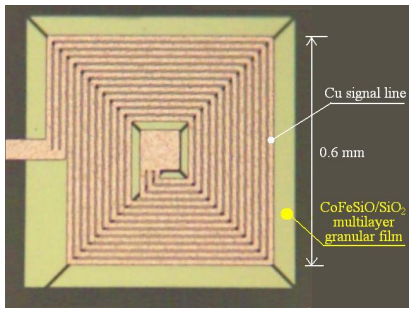

SONY
Cyber-shot
Carl Zeiss
Vario-Tessar
7.2
MEGA PIXELS


DELL


Meteosat DPP
1.69 GHz
FEUP 2002

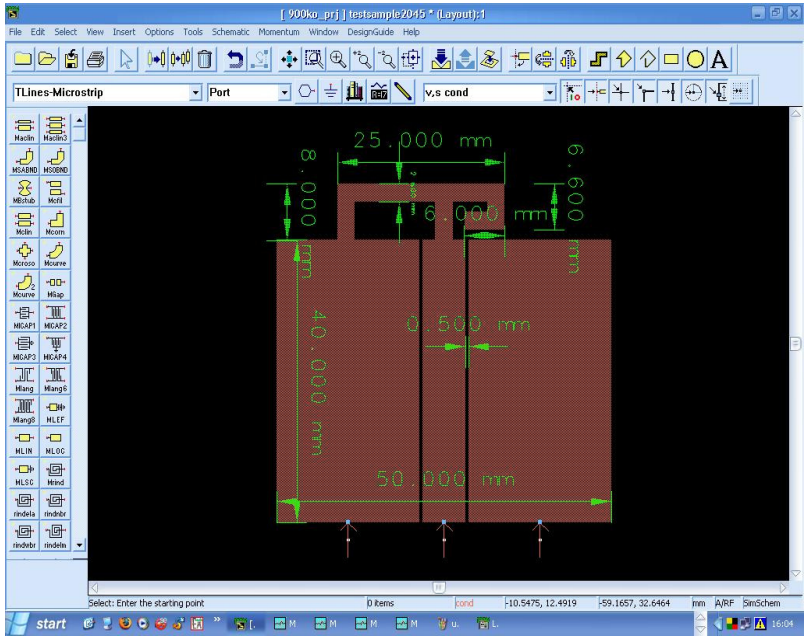

Cu signal line
0.6 mm
CoFeSiO/SiO2
multilayer
granular film

Design process

- several decisions
  - materials
  - geometrical dimensions
  - shape
  - constraints
    - space
    - cost
    - performance

Simulators

- implementation of models
- describe systems behavior
- help designers

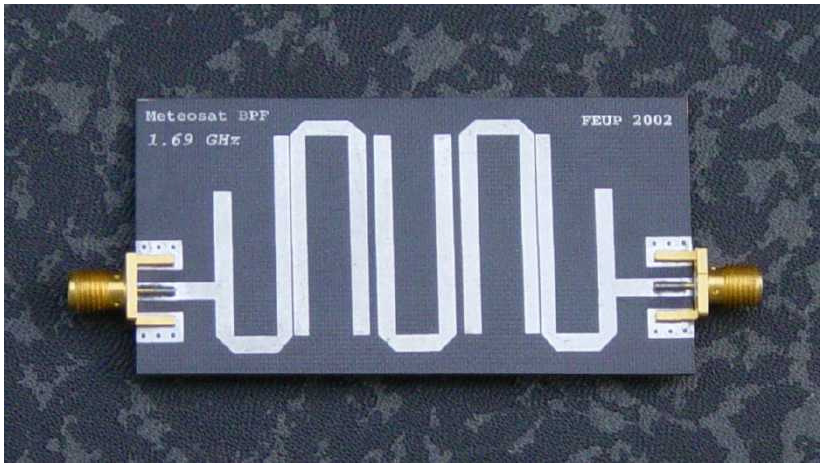


Measurements

- post tuning
- verification
- help designers

A typical design process requires

- design space optimization
- design space exploration
- sensitivity analysis
  - multiple simulations (measurements)
  - different design parameters values (e.g. layout features)



A typical design process requires

- Multiple simulations (measurements)
  - computationally expensive (time and memory)

- Can we do better?

- Yes
  - By parameterized macromodels

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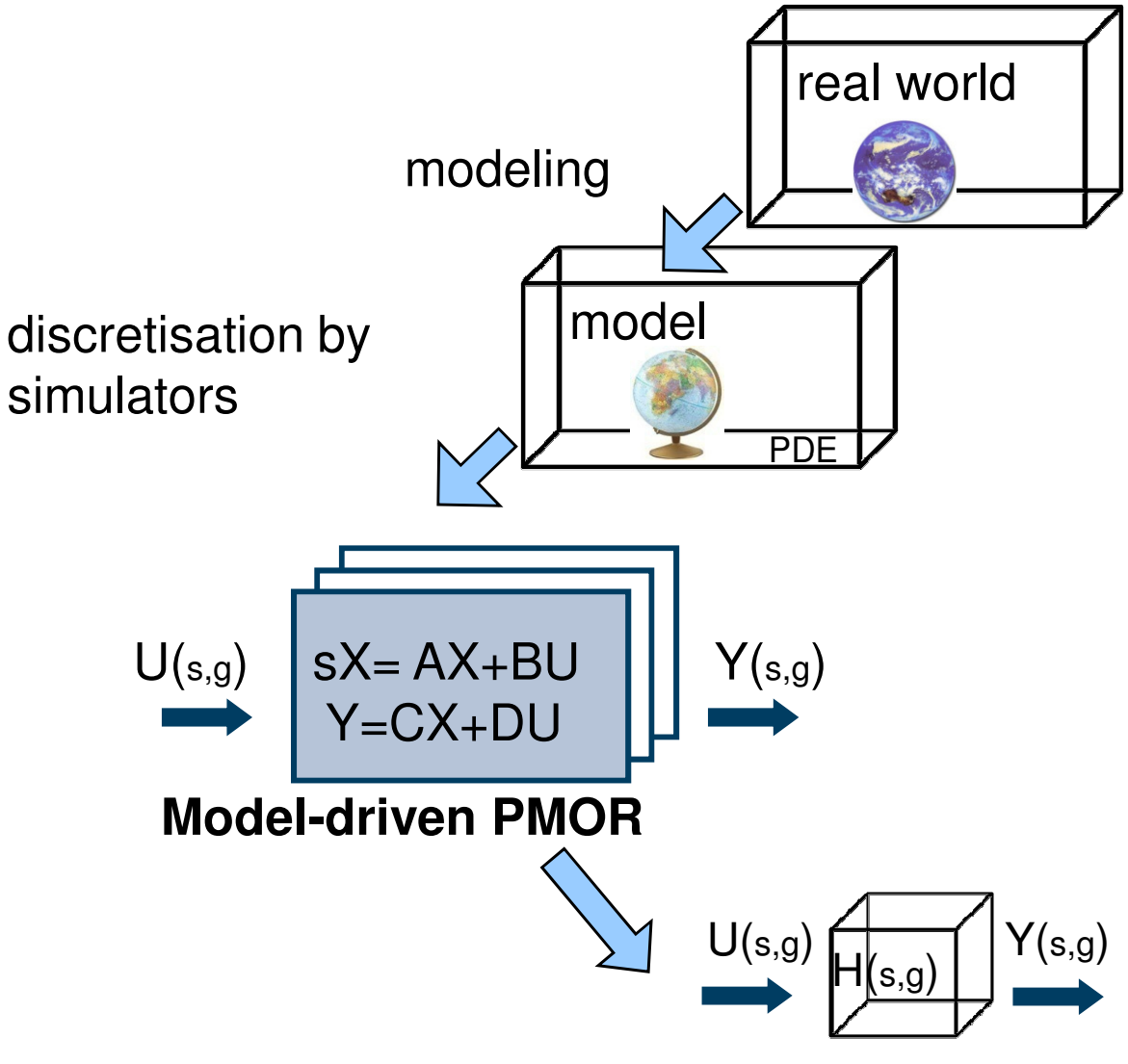
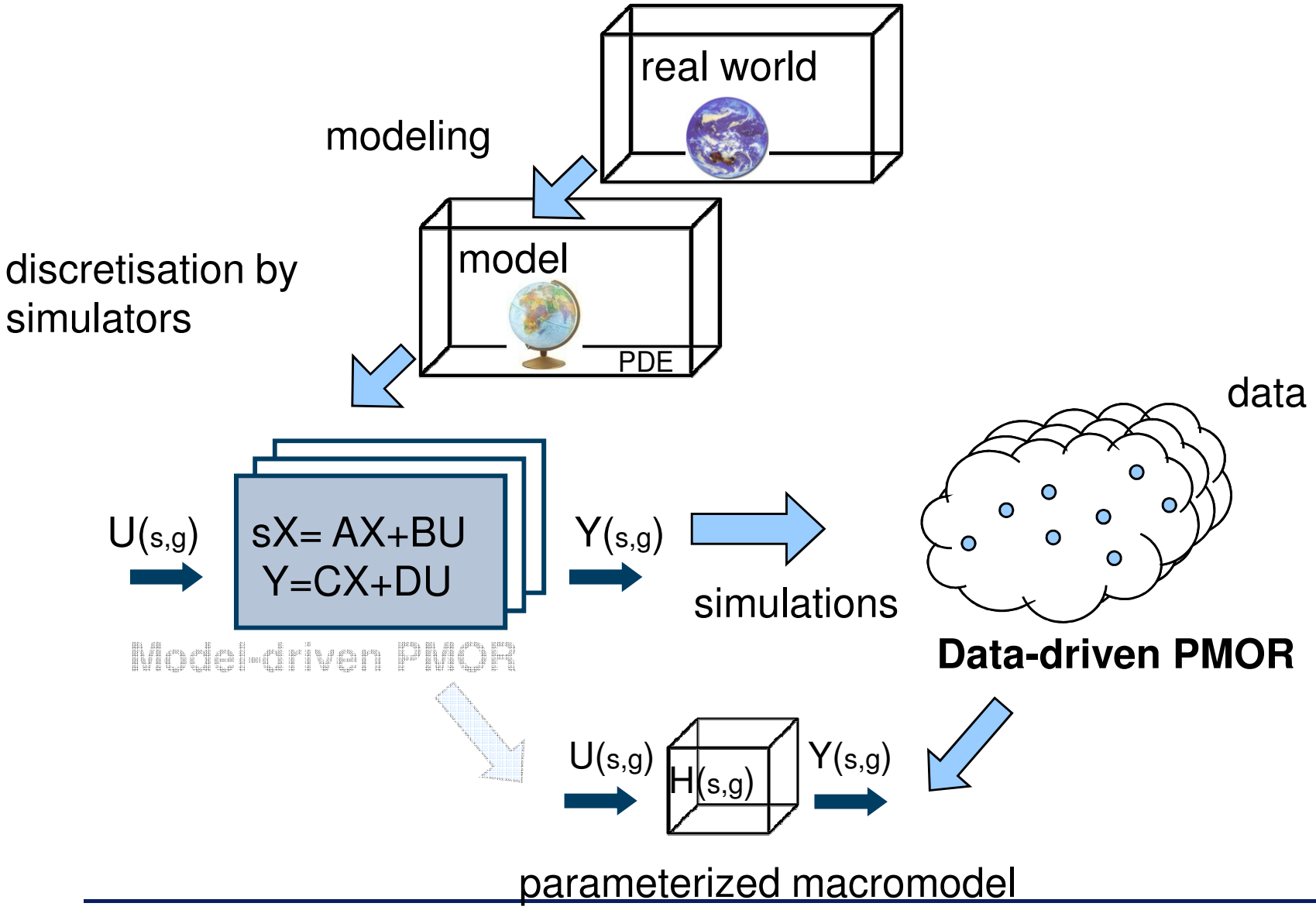

real world
modeling
model
discretisation by simulators
PDE
U(s,g)
sX= AX+BU
Y=CX+DU
Y(s,g)
Model-driven PMOR
U(s,g)
H(s,g)
Y(s,g)
parameterized macromodel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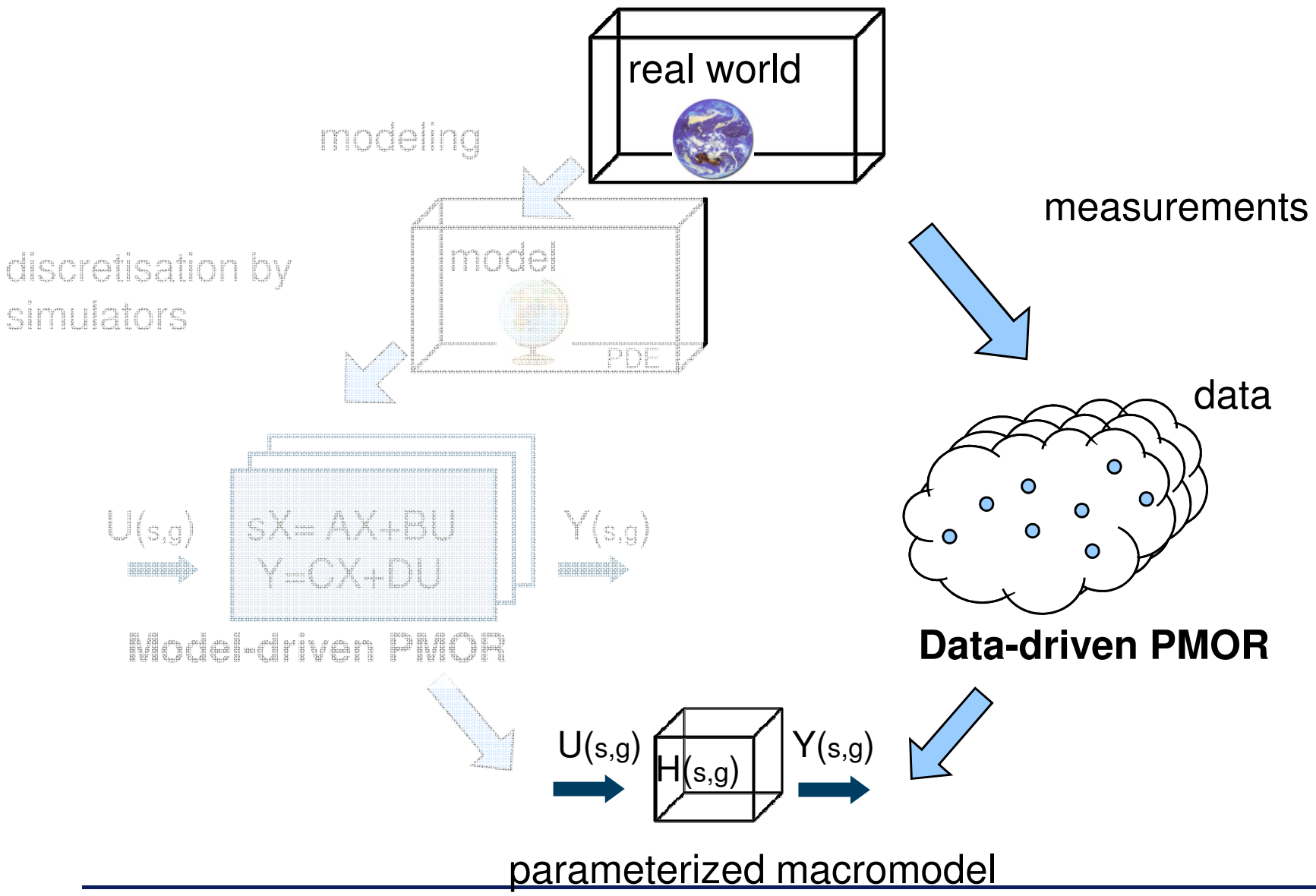
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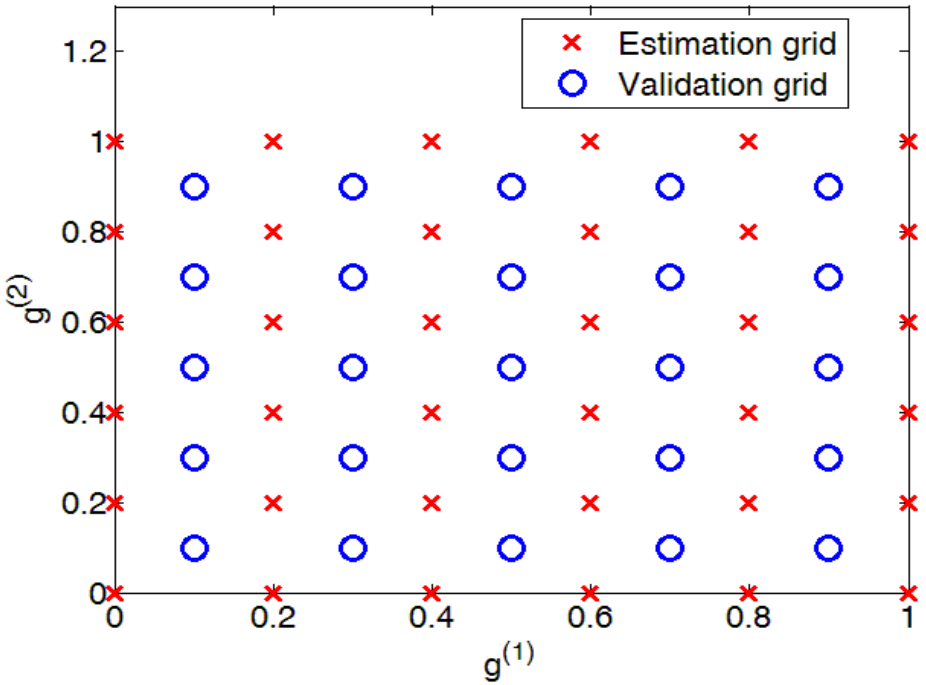
H(s,g)
Y(s,g)
parameterized macromodel

PMOR concepts

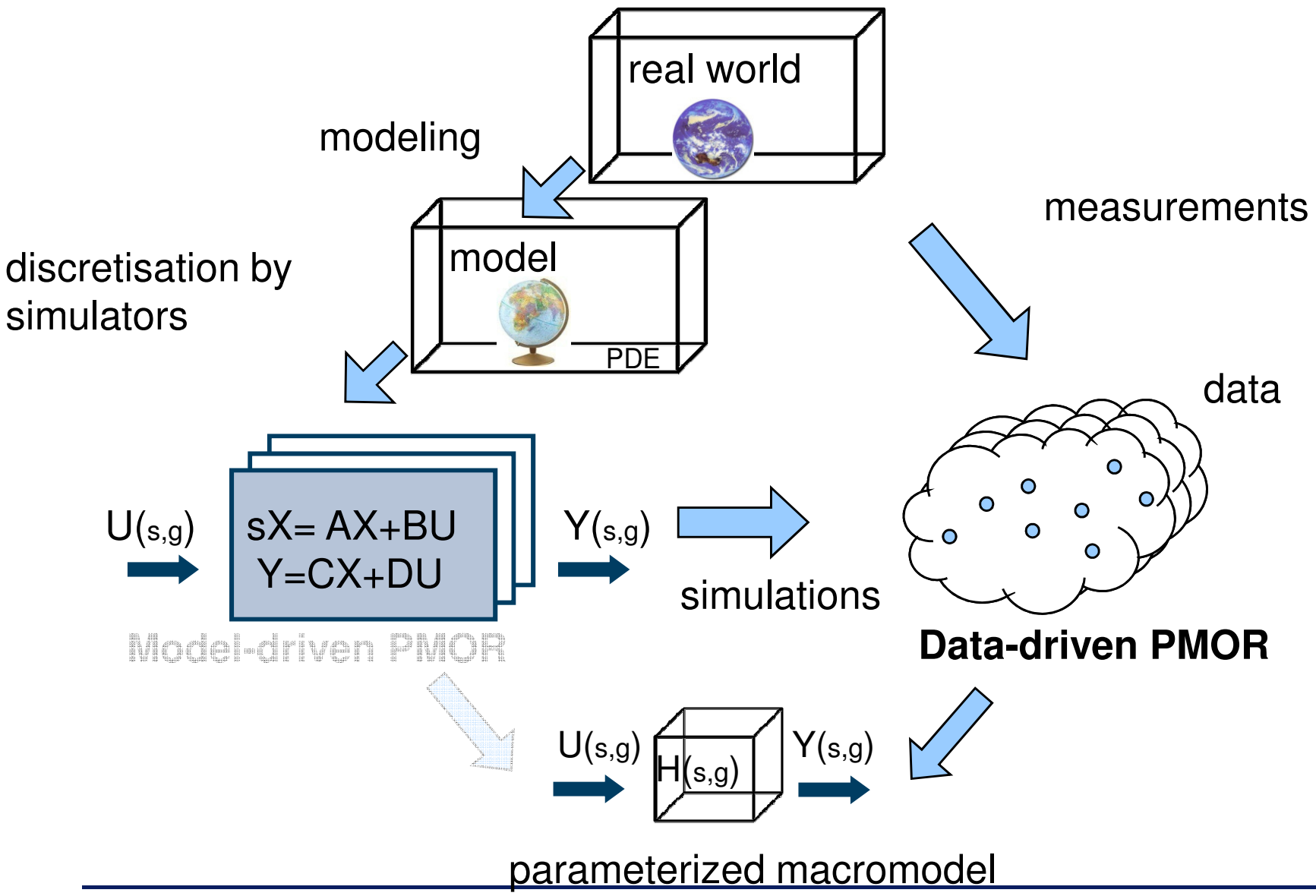
Two design space grids are used in the modeling process

- **estimation grid**
- **validation grid**

Design space



$$g = (g^{(n)})_{n=1}^{N}$$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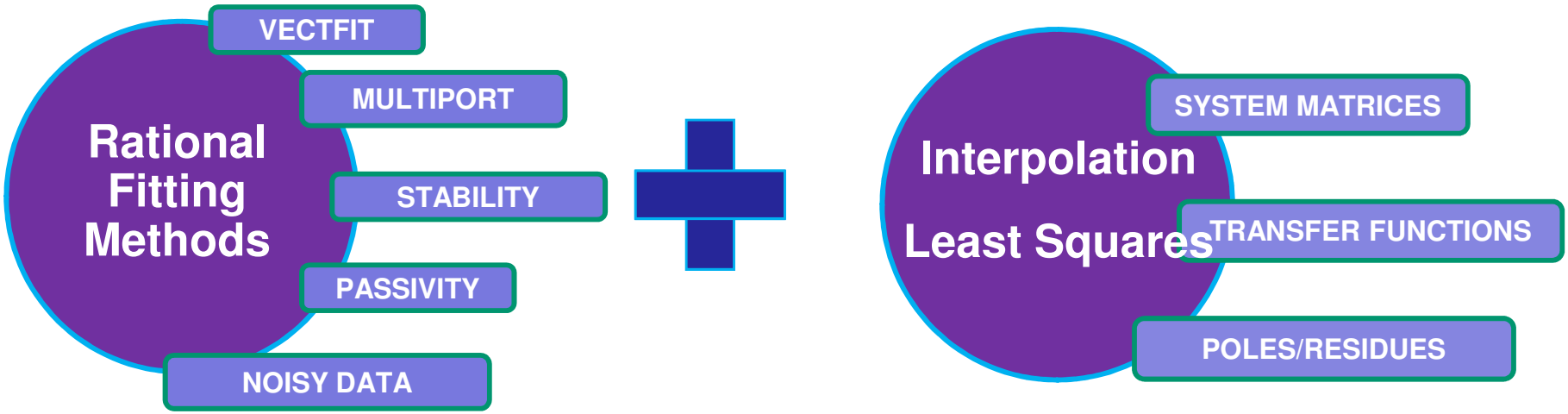
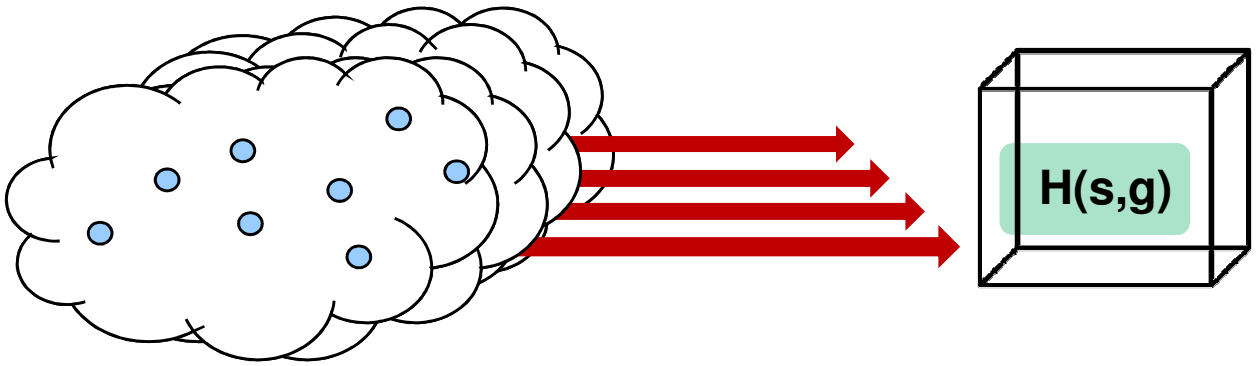
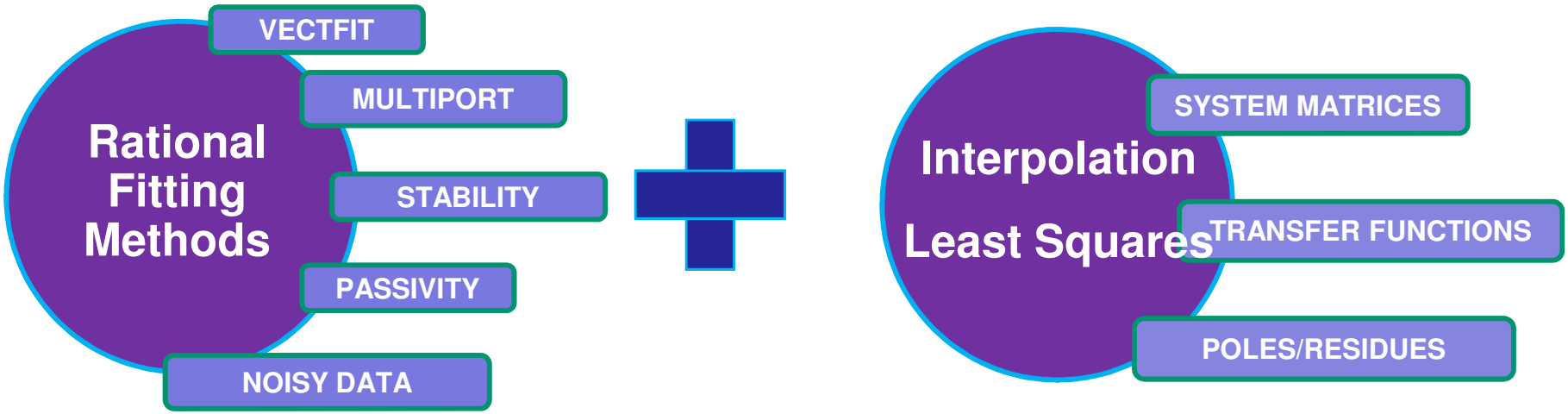


data-driven PMOR



scattered data

- accuracy
- efficiency
- stability guaranteed
- passivity guaranteed



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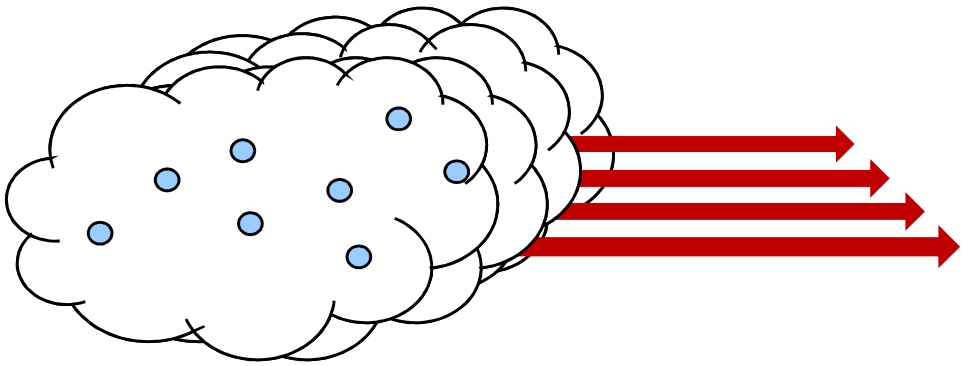
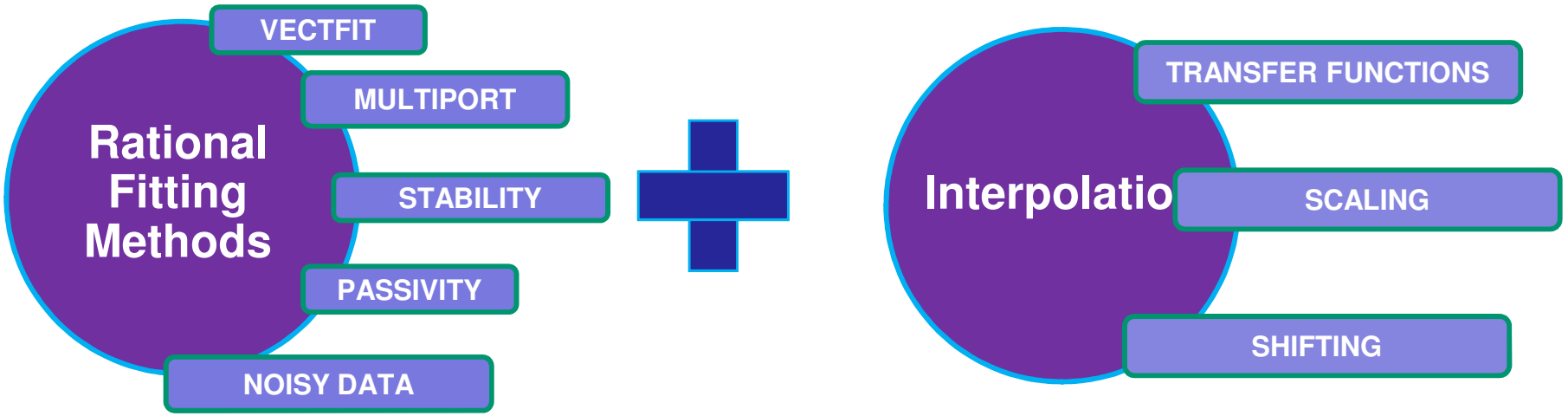


$$\mathbf{H}(s,\mathbf{g}) = \sum_{p=1}^{P} \frac{\mathbf{Q}(\mathbf{g})}{s - a_p(\mathbf{g})}$$

$$\mathbf{H}(s,\mathbf{g}) = \mathbf{C}(\mathbf{g})(s\mathbf{I} - \mathbf{A}(\mathbf{g}))^{-1}\mathbf{B}(\mathbf{g}) + \mathbf{D}(\mathbf{g})$$

scattered data



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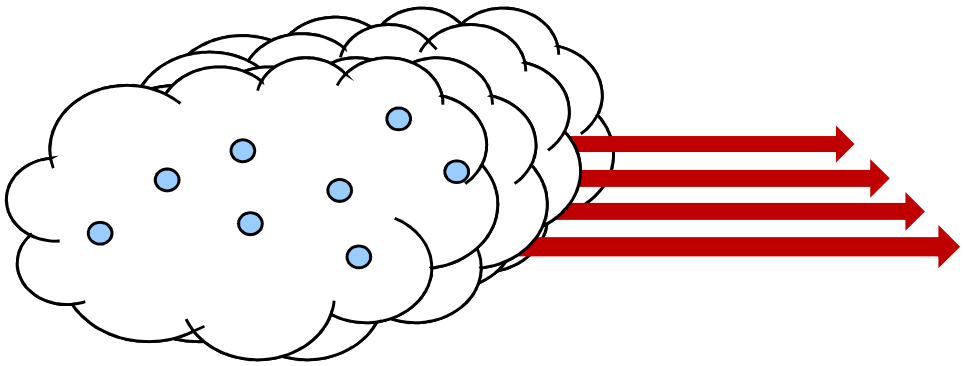

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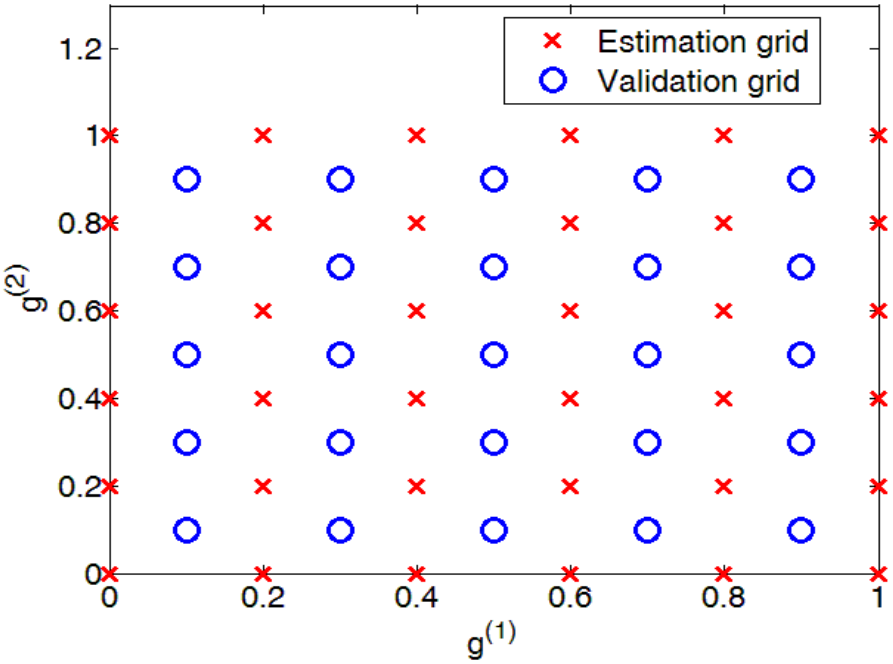
scattered data

Design space $g = (g^{(n)})_{n=1}^{N}$



Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$ in the estimation design space grid

↓

Compute scaling and frequency shifting coefficients $\alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i})$ in the estimation design space grid

↓

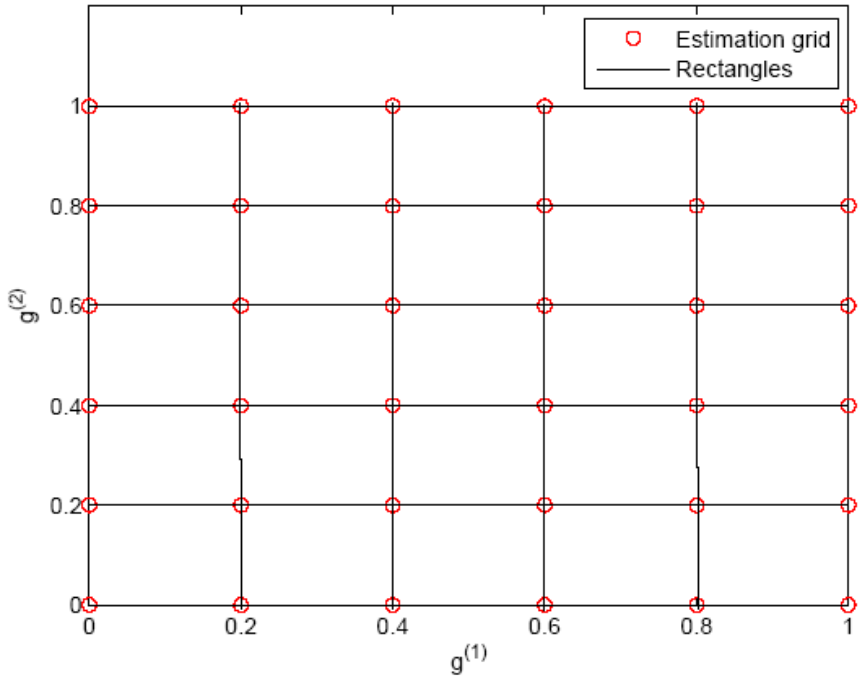
Multivariate interpolation of scaling and frequency shifting coefficients $\alpha_1(\mathbf{g}), \alpha_2(\mathbf{g})$

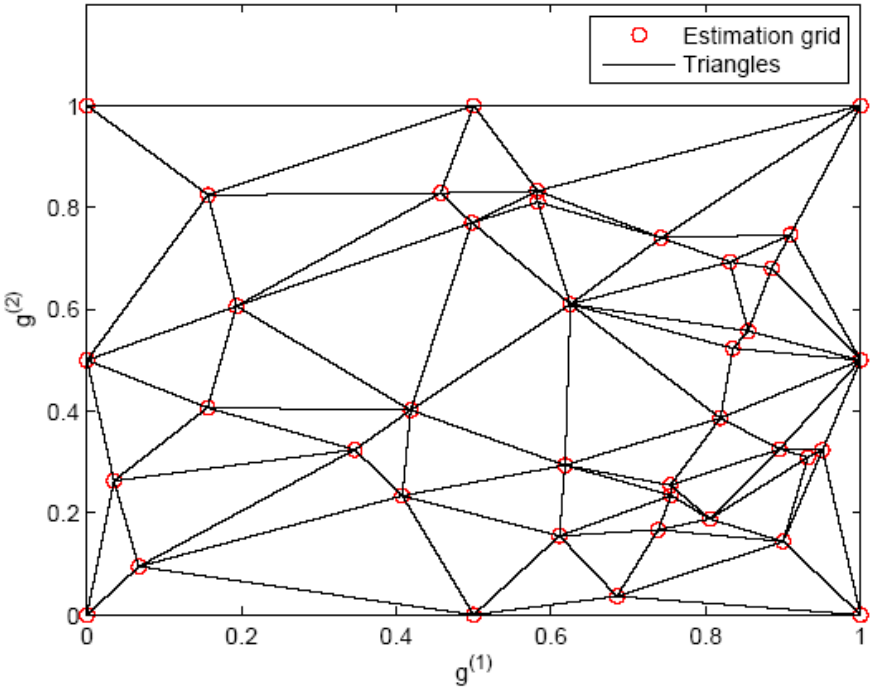
↓

Multivariate interpolation of scaled and shifted root macromodels $\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$

Features

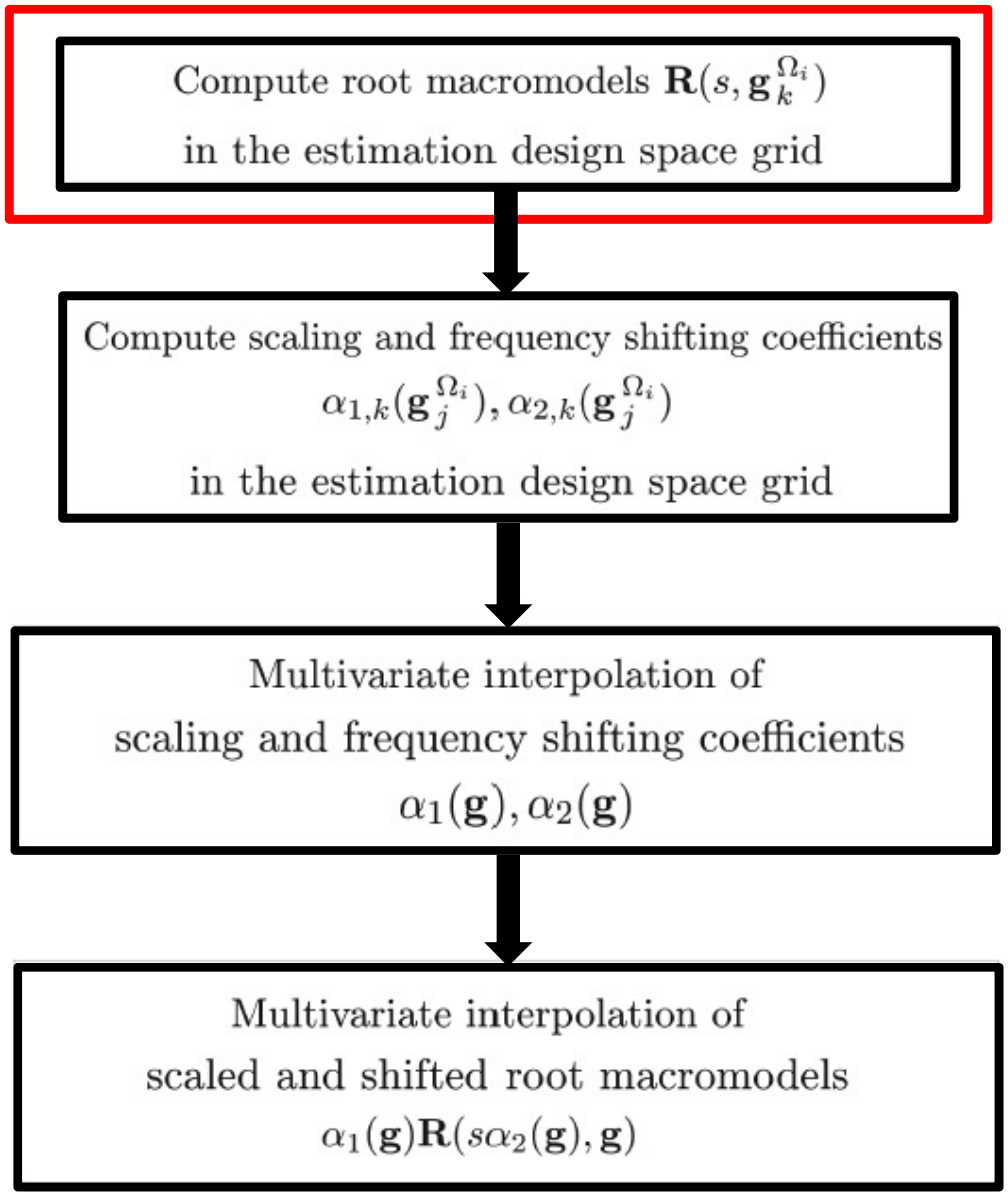
- **local approach (cell by cell)**





Features

- **local approach (cell by cell)**
- **independent from a specific state-space realization**
- **stability and passivity guaranteed over the design space**
- **suitable to robust adaptive sampling**
- **different flavours**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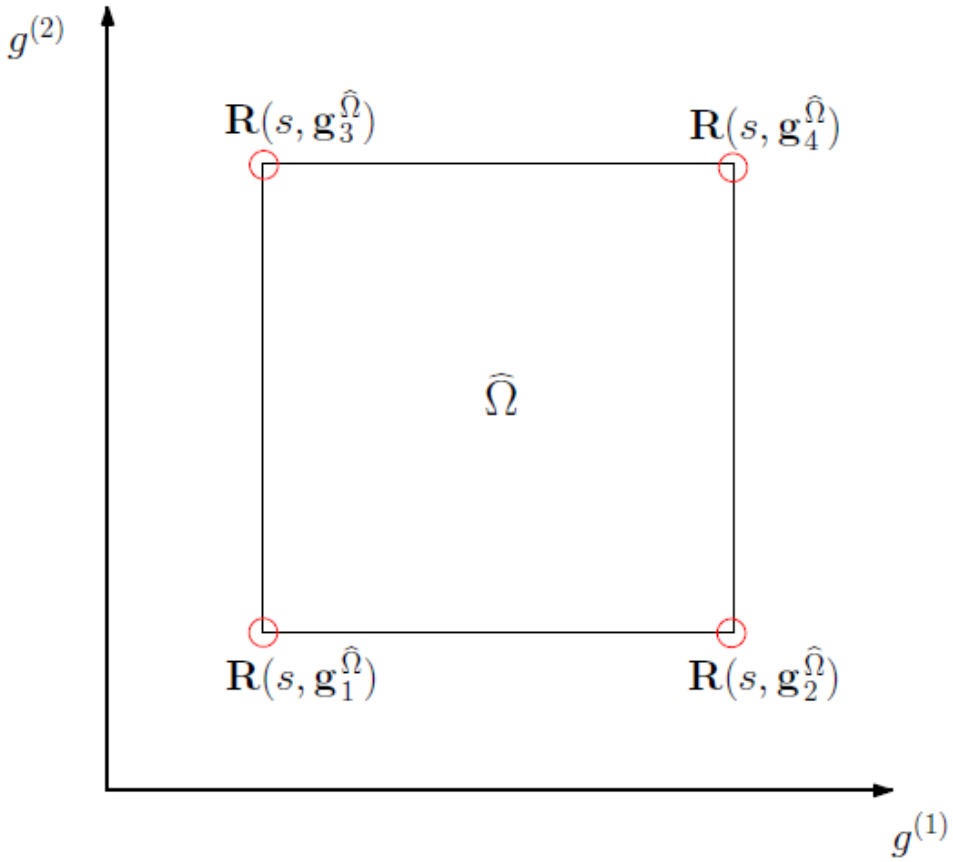
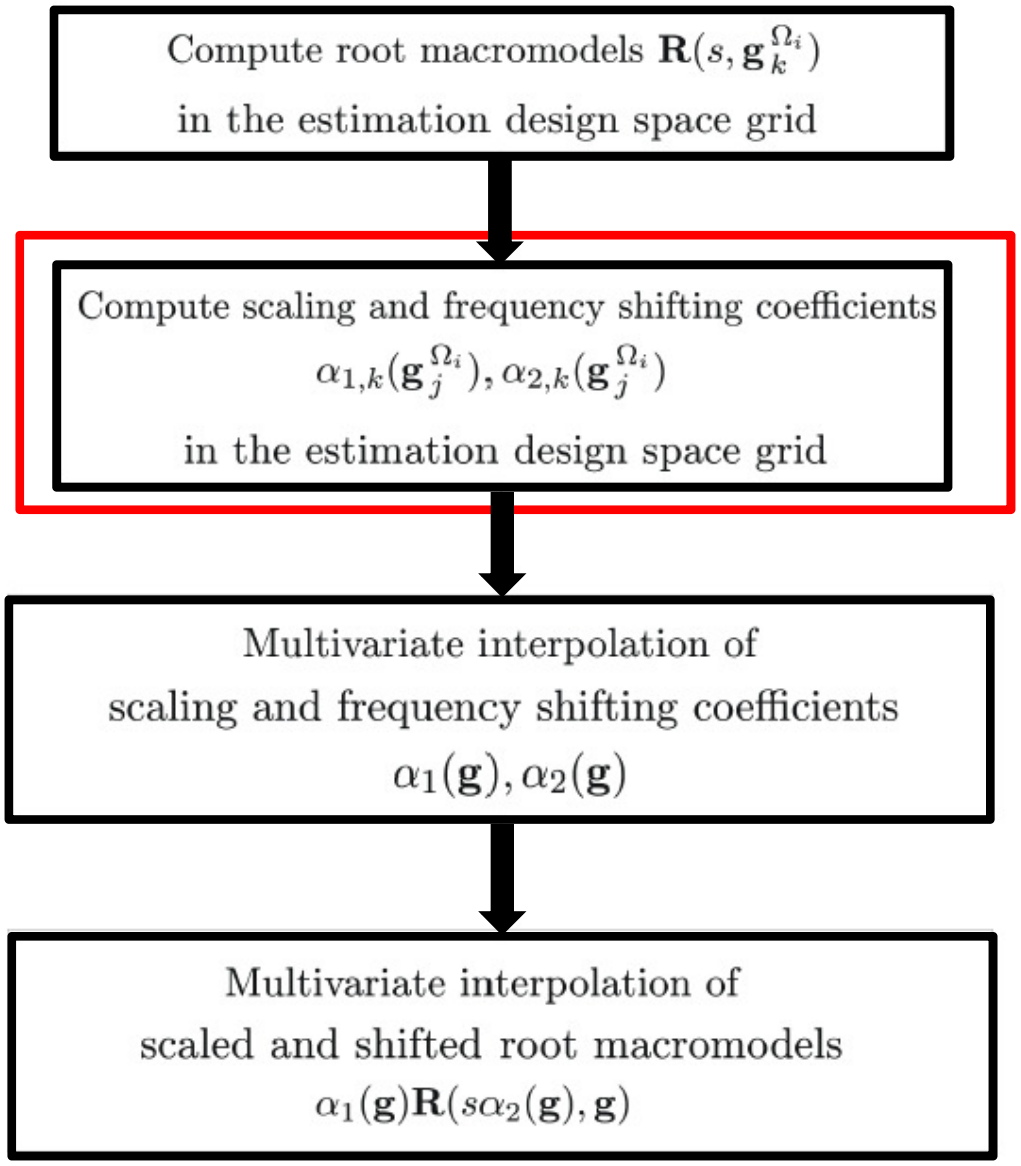
Compute scaling and frequency shifting coefficients $\alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i})$ in the estimation design space grid
Multivariate interpolation of scaling and frequency shifting coefficients $\alpha_1(\mathbf{g}), \alpha_2(\mathbf{g})$
Multivariate interpolation of scaled and shifted root macromodels $\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$



$$\mathbf{R}(s, \mathbf{g}_j^{\widehat{\Omega}}) = \mathbf{C}_0(\mathbf{g}_j^{\widehat{\Omega}}) + \sum_{n=1}^{N(\widehat{\Omega})} \frac{\mathbf{C}_n(\mathbf{g}_j^{\widehat{\Omega}})}{s - \mathbf{p}_n(\mathbf{g}_j^{\widehat{\Omega}})}$$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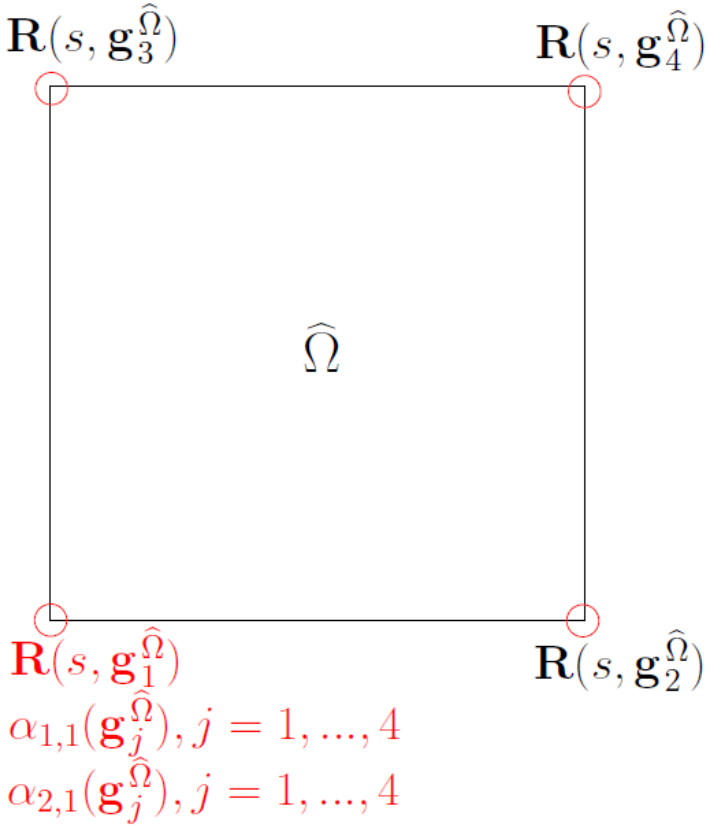
Multivariate interpolation of scaled and shifted root macromodels $\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$

$$\min_{\alpha_{1,k}(\mathbf{g}_j^{\widehat{\Omega}}),\alpha_{2,k}(\mathbf{g}_j^{\widehat{\Omega}})} Err(\widetilde{\mathbf{R}}(s,\boldsymbol{g}_k^{\widehat{\Omega}}),\mathbf{R}(s,\boldsymbol{g}_j^{\widehat{\Omega}}))$$

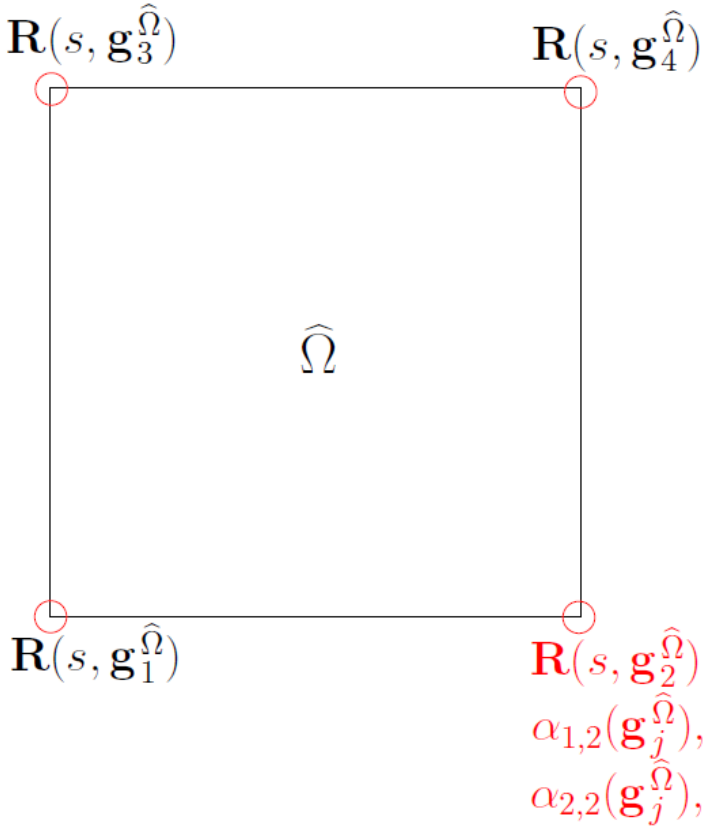
$$\widetilde{\mathbf{R}}(s,\boldsymbol{g}_k^{\widehat{\Omega}}) = \alpha_{1,k}(\boldsymbol{g}_j^{\widehat{\Omega}})\mathbf{R}(s\alpha_{2,k}(\boldsymbol{g}_j^{\widehat{\Omega}}),\boldsymbol{g}_k^{\widehat{\Omega}})$$

$$\alpha_{1,k}(\boldsymbol{g}_j^{\widehat{\Omega}}) = \alpha_{2,k}(\boldsymbol{g}_j^{\widehat{\Omega}}) = 1,\ j = k$$



$\alpha_{1,1}(\mathbf{g}_j^{\widehat{\Omega}}), j = 1,...,4$

$\alpha_{2,1}(\mathbf{g}_j^{\widehat{\Omega}}), j = 1,...,4$



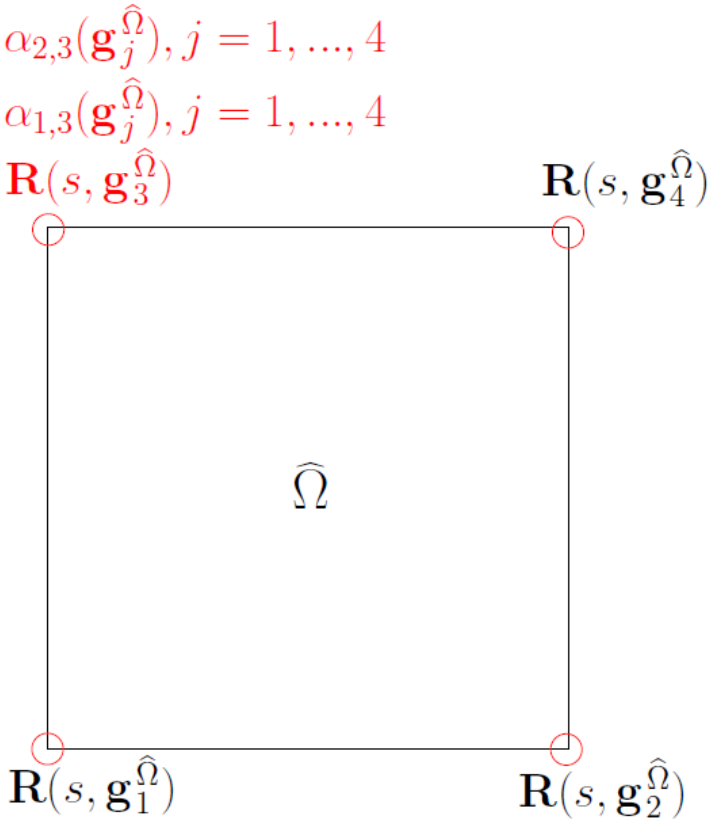
$\alpha_{1,2}(\mathbf{g}_j^{\widehat{\Omega}}), j = 1,...,4$

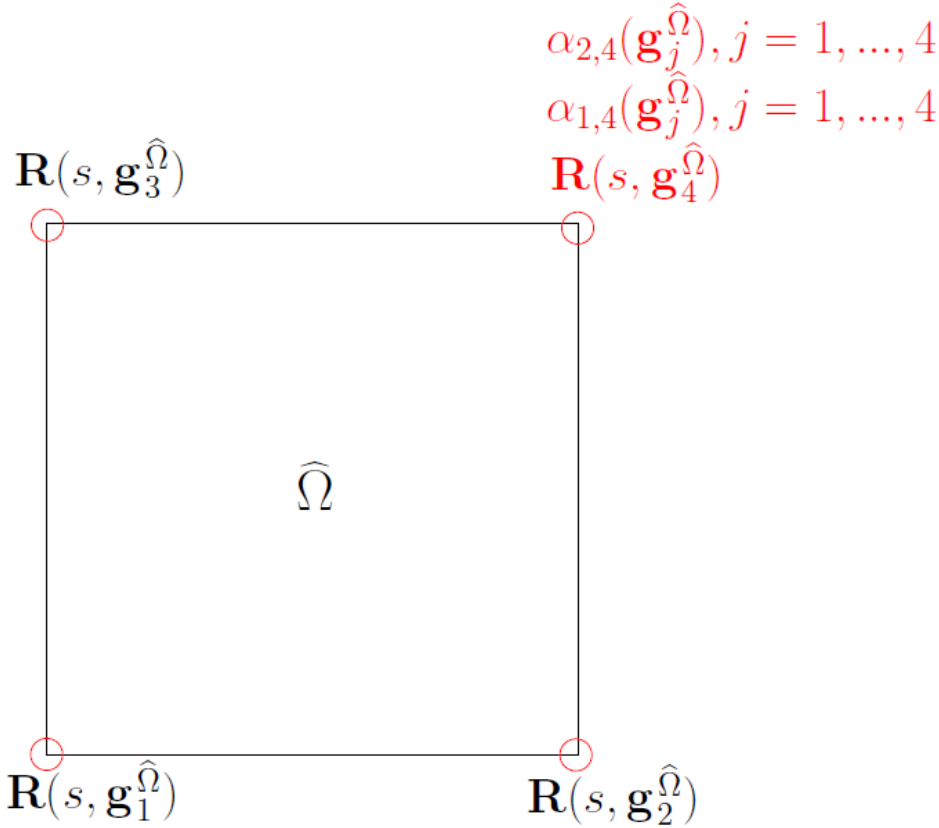
$\alpha_{2,2}(\mathbf{g}_j^{\widehat{\Omega}}), j = 1,...,4$

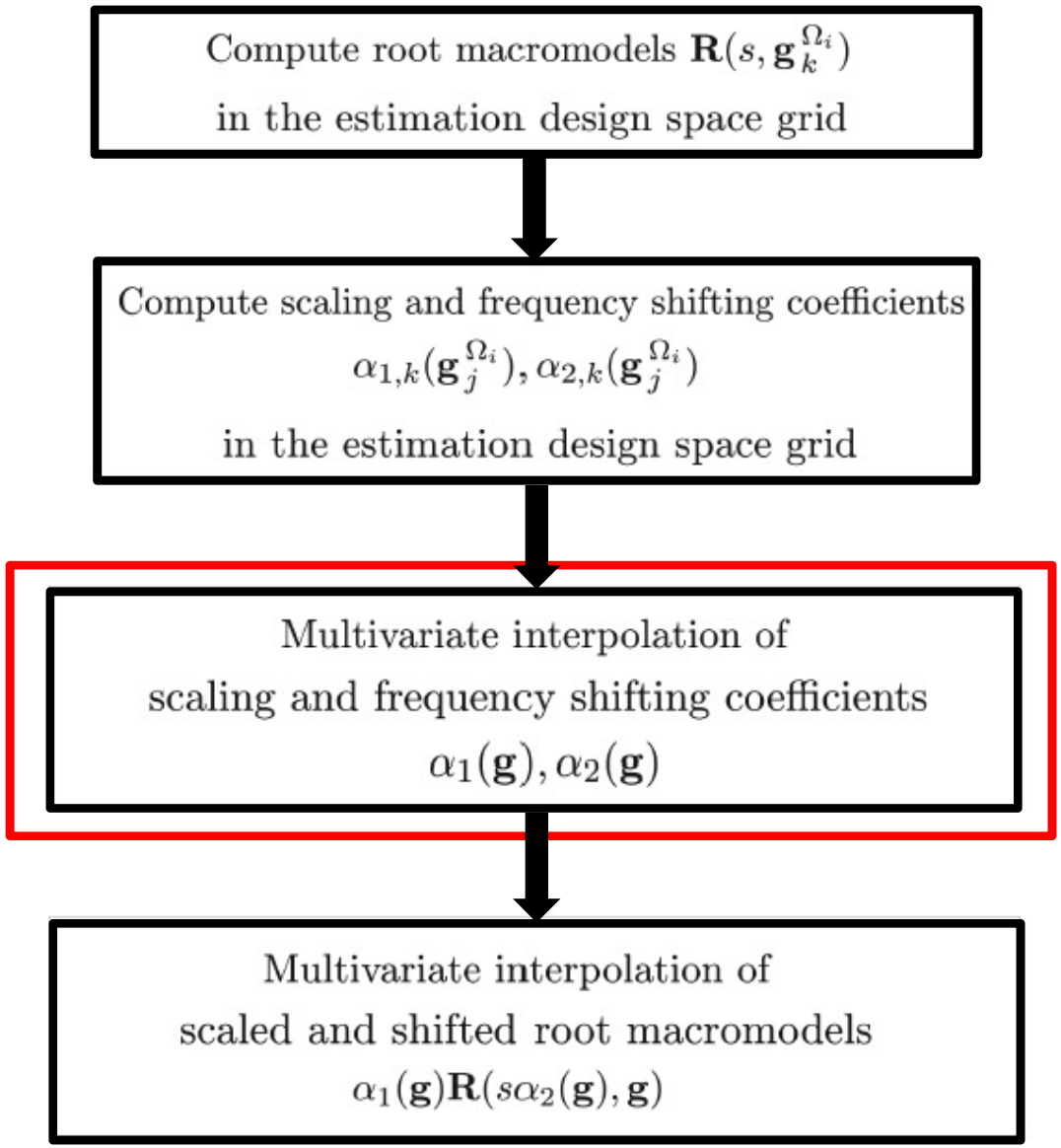
$$\min_{\alpha_{1,k}(\mathbf{g}_j^{\widehat{\Omega}}),\alpha_{2,k}(\mathbf{g}_j^{\widehat{\Omega}})} Err(\widetilde{\mathbf{R}}(s,\boldsymbol{g}_k^{\widehat{\Omega}}),\mathbf{R}(s,\boldsymbol{g}_j^{\widehat{\Omega}}))$$

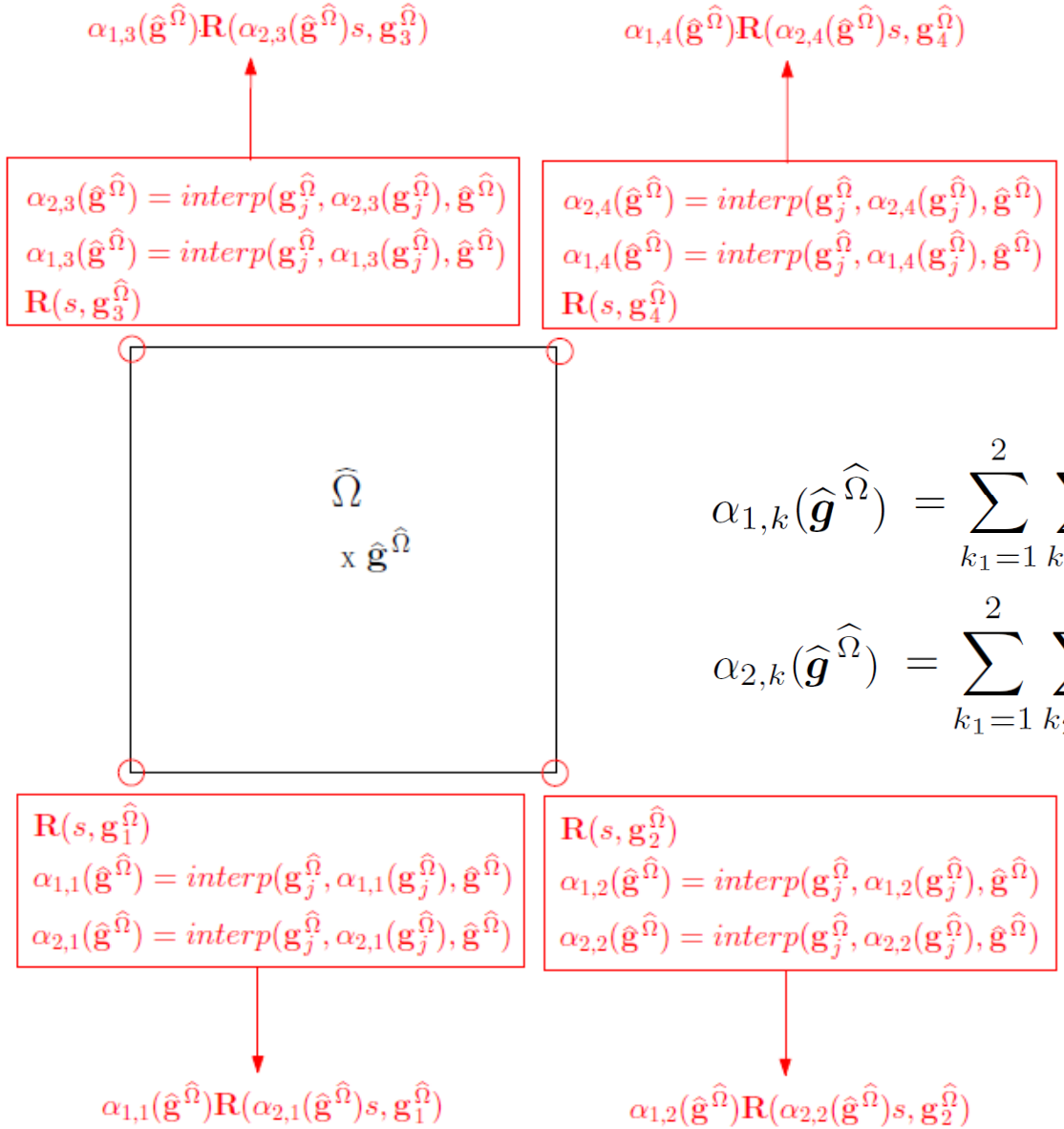
$$\widetilde{\mathbf{R}}(s,\boldsymbol{g}_k^{\widehat{\Omega}}) = \alpha_{1,k}(\boldsymbol{g}_j^{\widehat{\Omega}})\mathbf{R}(s\alpha_{2,k}(\boldsymbol{g}_j^{\widehat{\Omega}}),\boldsymbol{g}_k^{\widehat{\Omega}})$$

$$\alpha_{1,k}(\boldsymbol{g}_j^{\widehat{\Omega}}) = \alpha_{2,k}(\boldsymbol{g}_j^{\widehat{\Omega}}) = 1,\ j = k$$



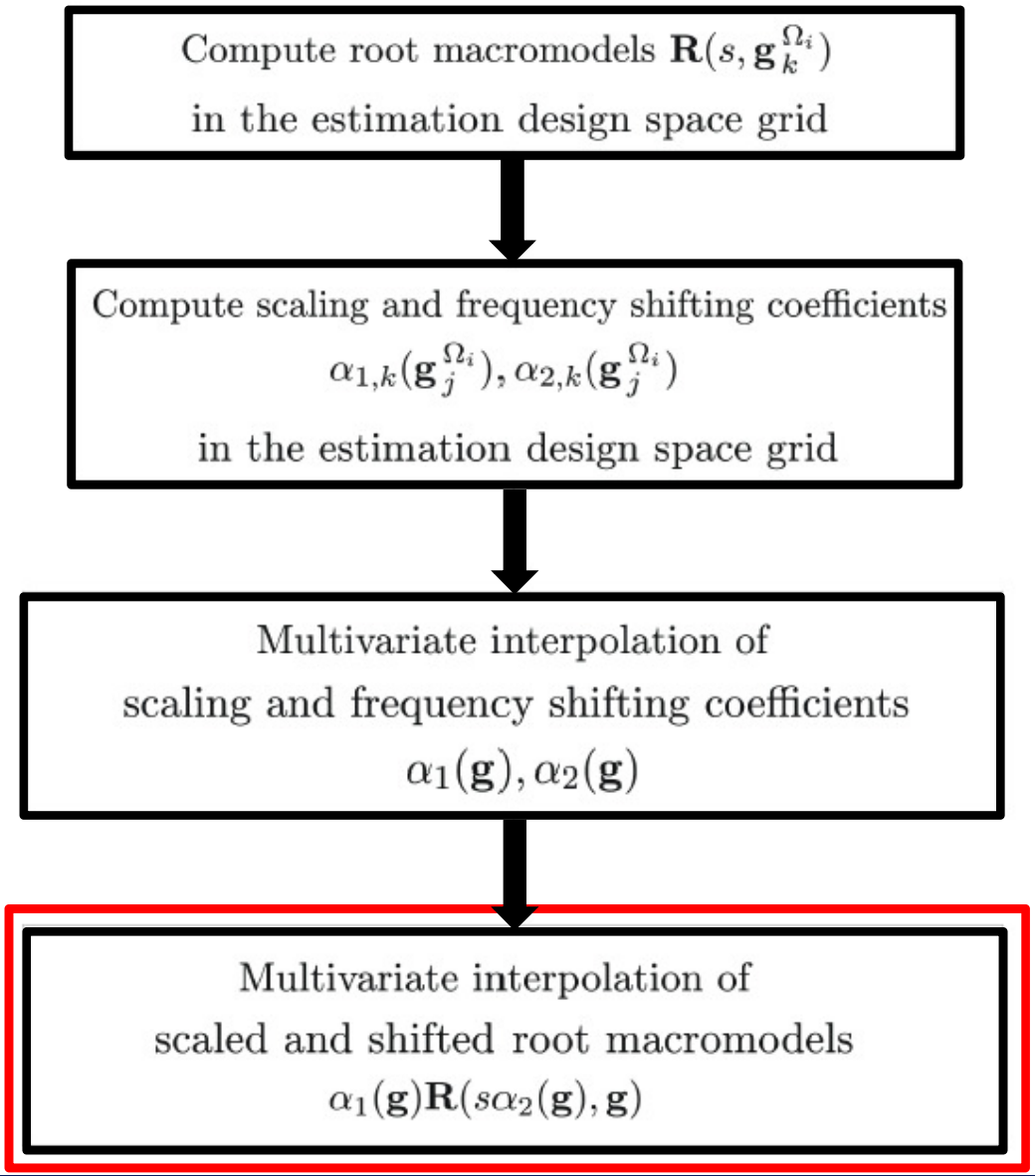



Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$ in the estimation design space grid
Compute scaling and frequency shifting coefficients $\alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i})$ in the estimation design space grid
Multivariate interpolation of scaling and frequency shifting coefficients $\alpha_1(\mathbf{g}), \alpha_2(\mathbf{g})$
Multivariate interpolation of scaled and shifted root macromodels $\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$



$$\alpha_{1,k}(\widehat{\boldsymbol{g}}^{\widehat{\Omega}}) = \sum_{k_1=1}^{2}\sum_{k_2=1}^{2} \alpha_{1,k}((g_{k_1}^{(1)}, g_{k_2}^{(2)})^{\widehat{\Omega}})\ell_{k_1}(g^{(1)})\ell_{k_2}(g^{(2)})$$

$$\alpha_{2,k}(\widehat{\boldsymbol{g}}^{\widehat{\Omega}}) = \sum_{k_1=1}^{2}\sum_{k_2=1}^{2} \alpha_{2,k}((g_{k_1}^{(1)}, g_{k_2}^{(2)})^{\widehat{\Omega}})\ell_{k_1}(g^{(1)})\ell_{k_2}(g^{(2)})$$


Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$
in the estimation design space grid
Compute scaling and frequency shifting coefficients
$\alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i})$
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Multivariate interpolation of
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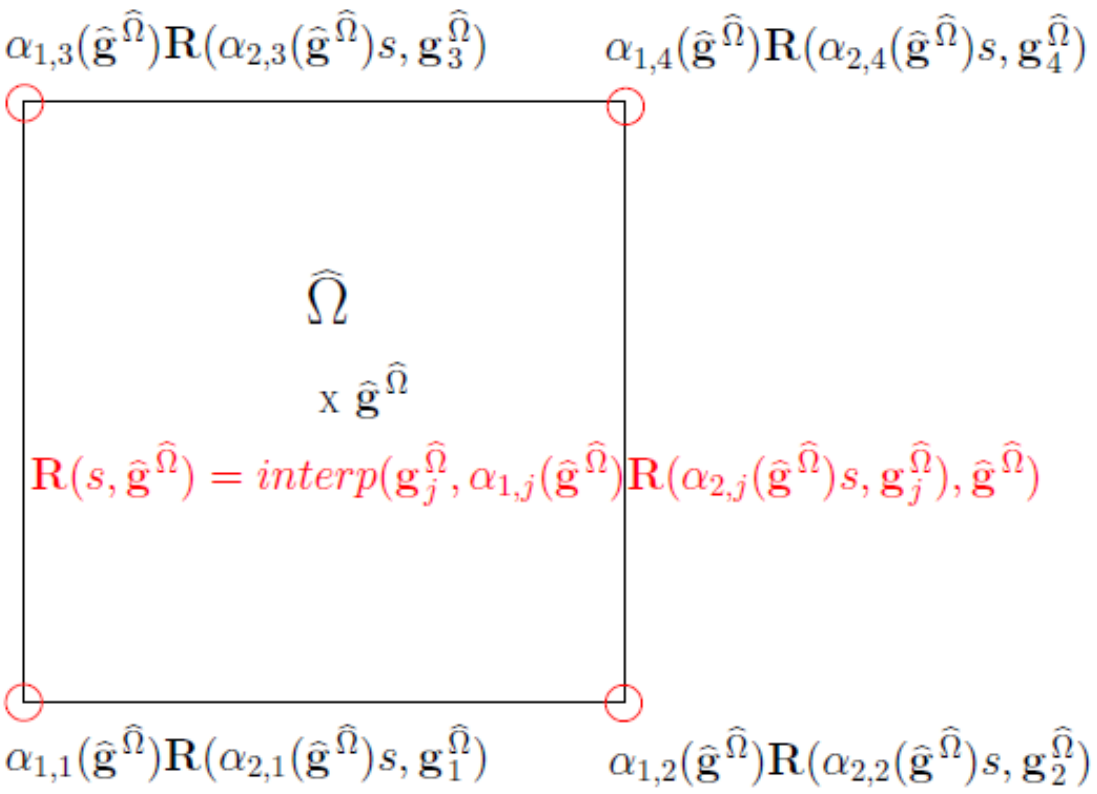
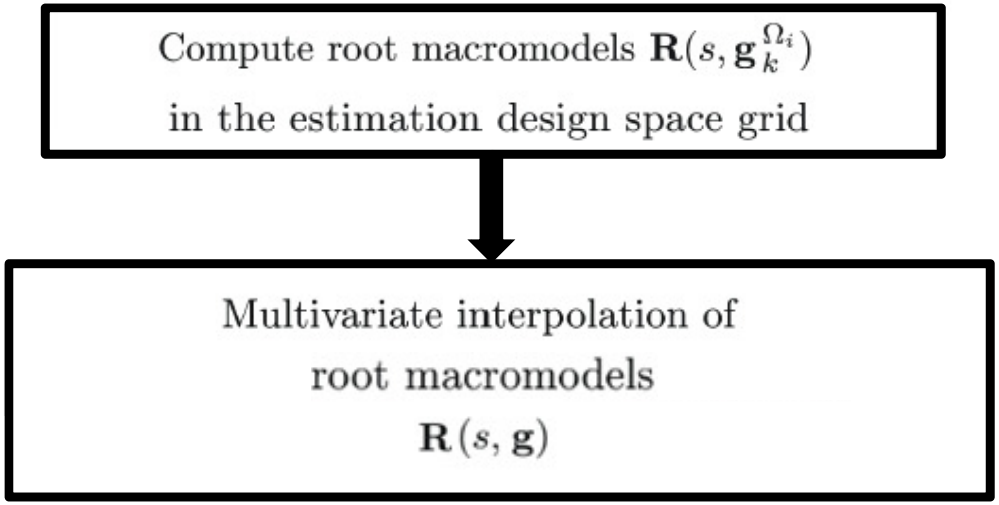
Multivariate interpolation of
scaled and shifted root macromodels
$\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$



$$\mathbf{R}(s, \widehat{g}^{\widehat{\Omega}}) = \sum_{k_1=1}^{2} \sum_{k_2=1}^{2} \widetilde{\mathbf{R}}(s, (g_{k_1}^{(1)}, g_{k_2}^{(2)})^{\widehat{\Omega}}) \ell_{k_1}(g^{(1)}) \ell_{k_2}(g^{(2)})$$

Standard Interpolation



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- **SI example**

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VECTFIT

MULTIPORT

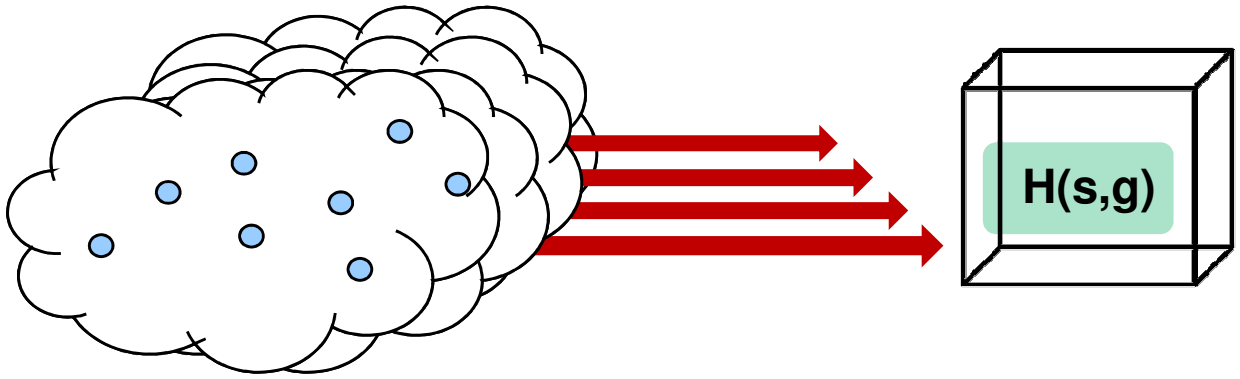
Rational Fitting Methods

+

SYSTEM MATRICES

Interpolation Least Squares

data-driven PMOR



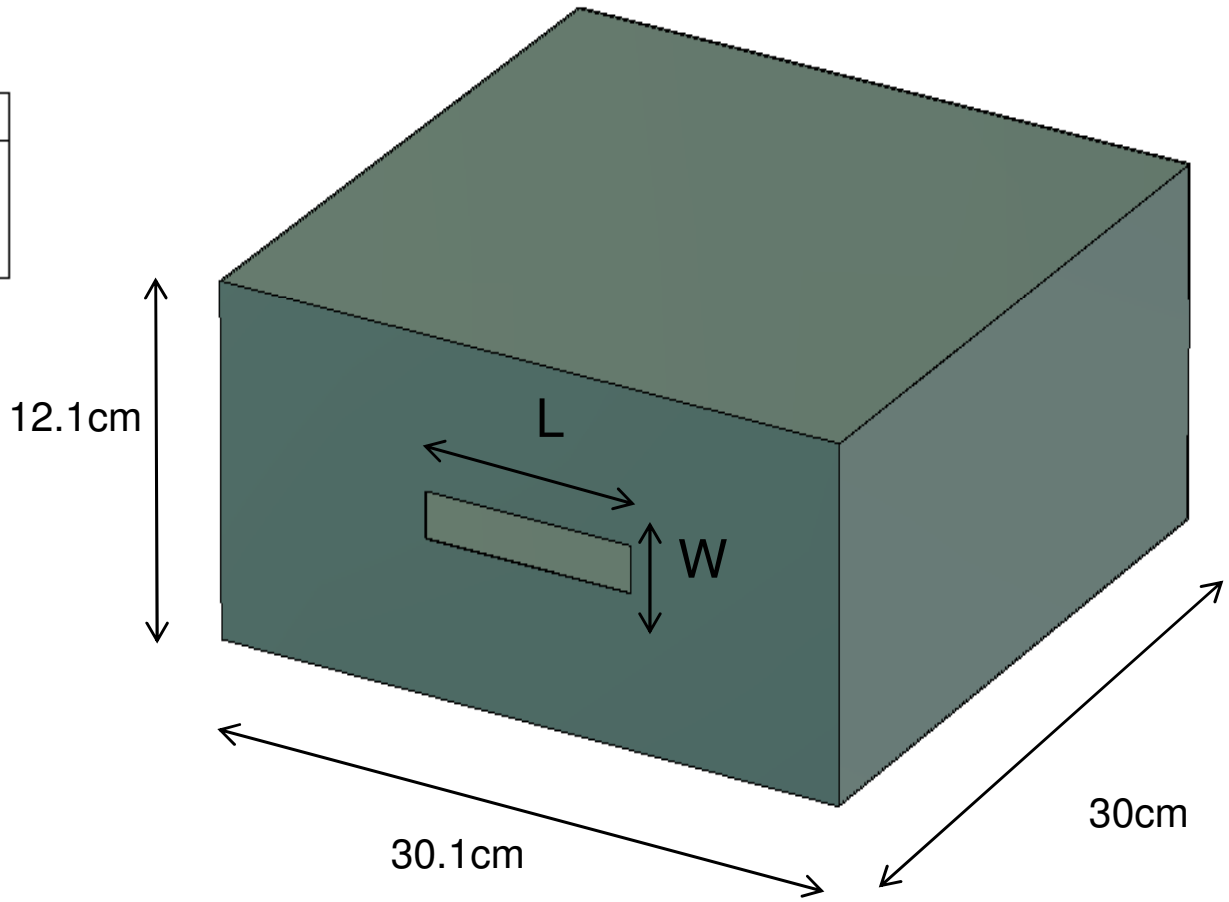
scattered data

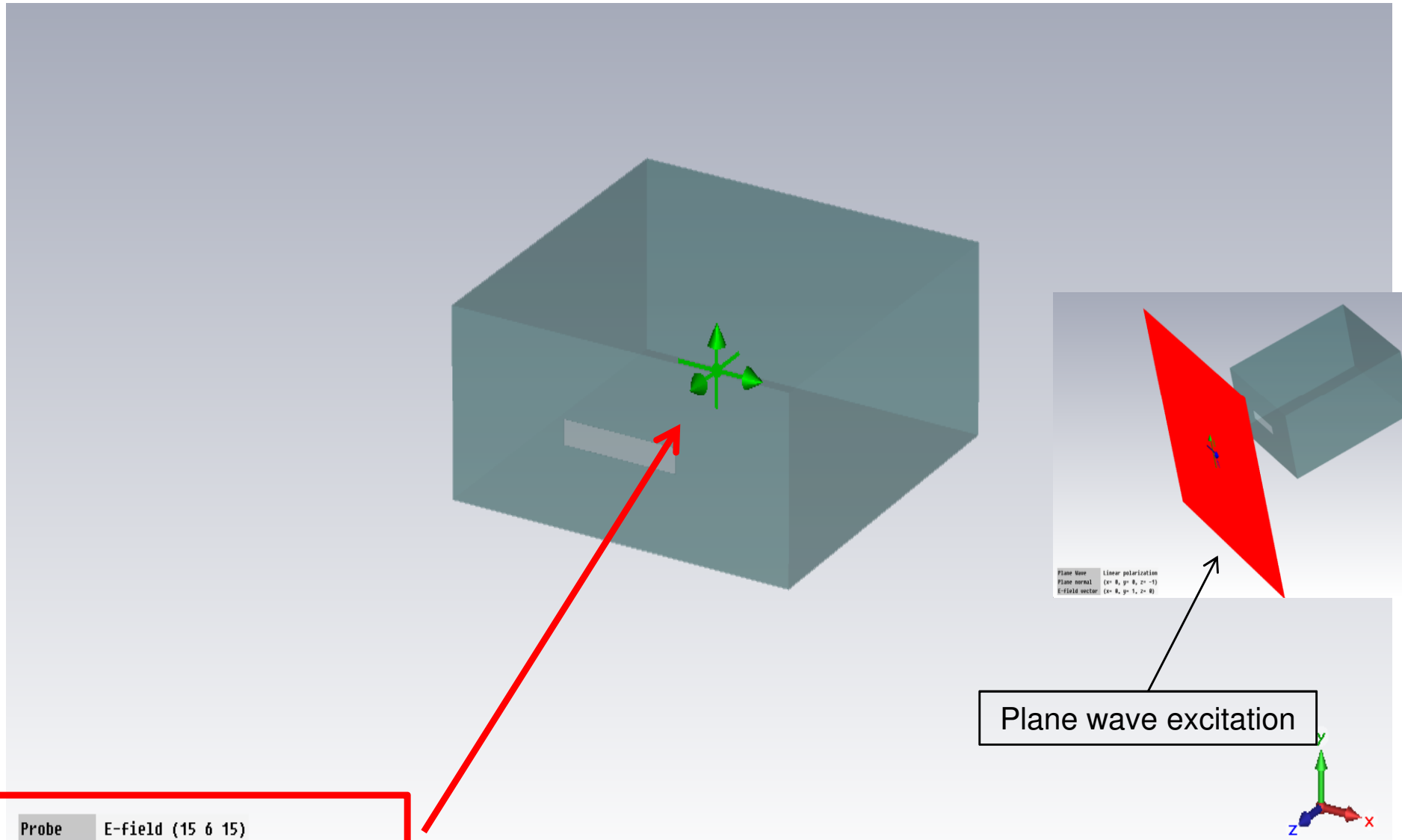
$$\mathbf{H}(s,\mathbf{g}) = \sum_{p=1}^{P} \frac{\mathbf{Q}(\mathbf{g})}{s - a_p(\mathbf{g})}$$

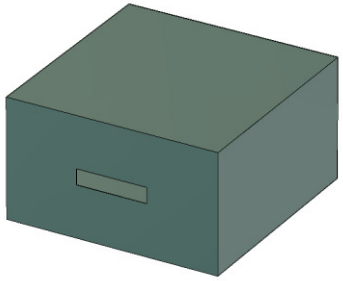
$$\mathbf{H}(s,\mathbf{g}) = \mathbf{C}(\mathbf{g})(s\mathbf{I} - \mathbf{A}(\mathbf{g}))^{-1}\mathbf{B}(\mathbf{g}) + \mathbf{D}(\mathbf{g})$$

3D example: Enclosure

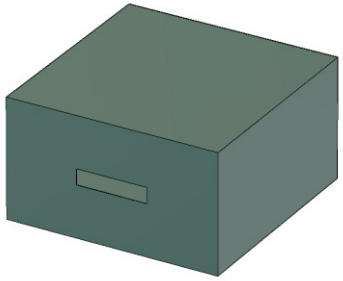
Parameter	Min	Max
Frequency (freq)	0 Hz	1 GHz
Length (L)	10 cm	20 cm
Width (W)	0.8 cm	2.8 cm




Plane wave excitation
Probe E-field (15 6 15)
Type Efield
Position 15, 6, 15



Step	CPU time
Estimation grid by solver (6×6) (L,W)	2 h 25 min 48 s
Validation grid by solver (5×5) (L,W)	1 h 41 min 15 s
Building model	3.08 s
Validating model	0.9 s
Evaluating solver (one frequency response)	4 min 3 s
Evaluating model (one frequency response)	7.2 ms



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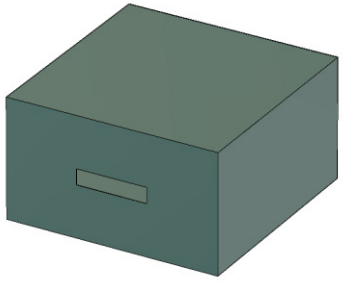
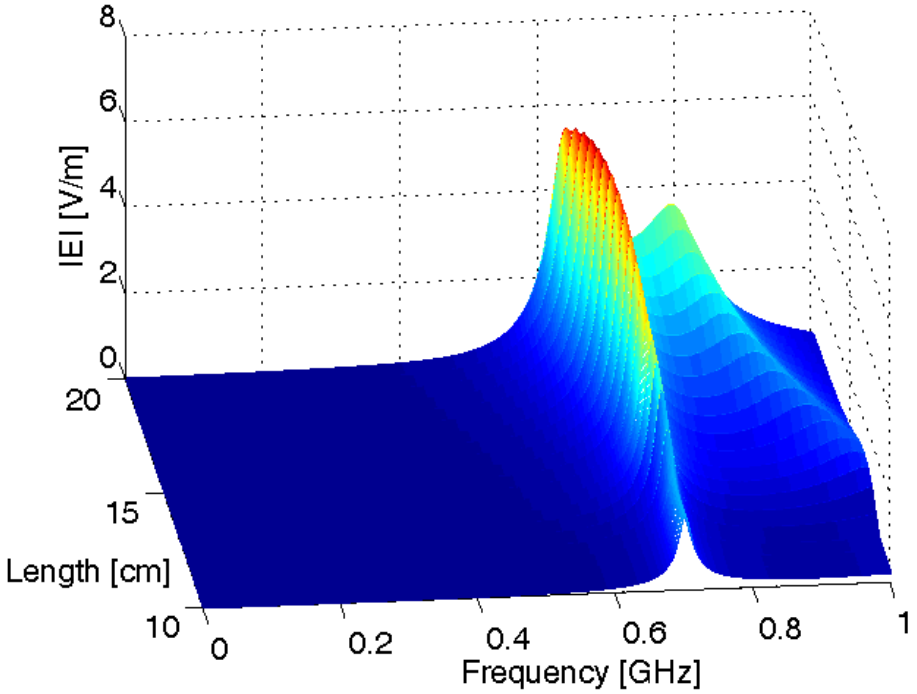
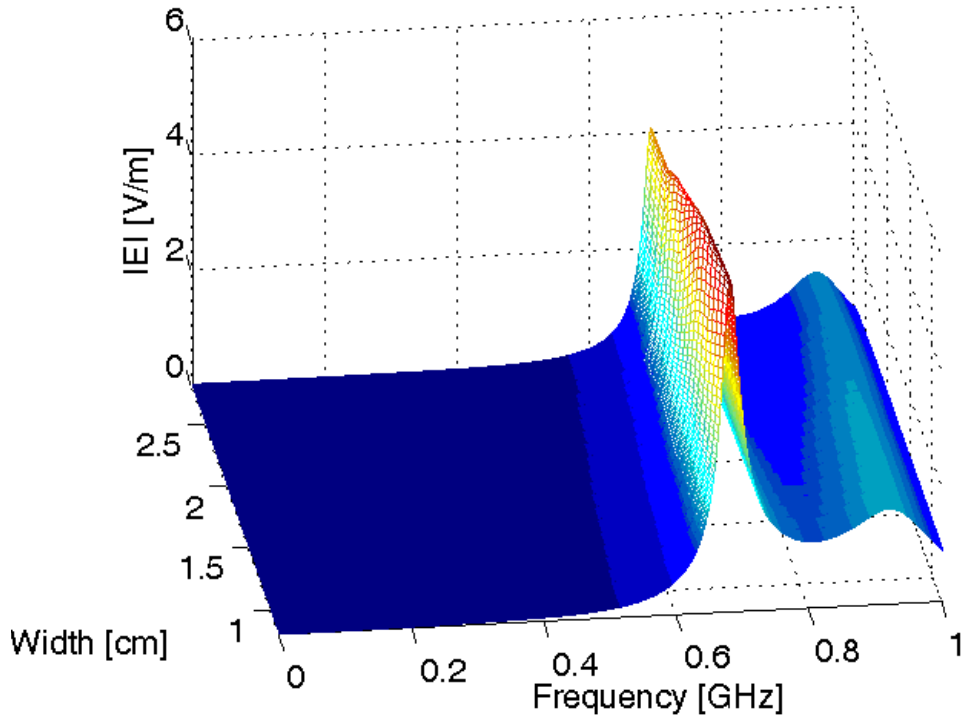
Speed-up 33750 x

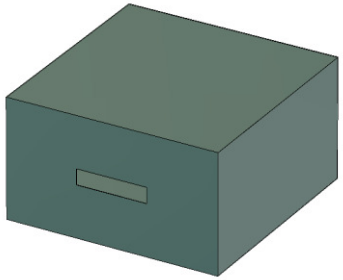


W=1.8 cm

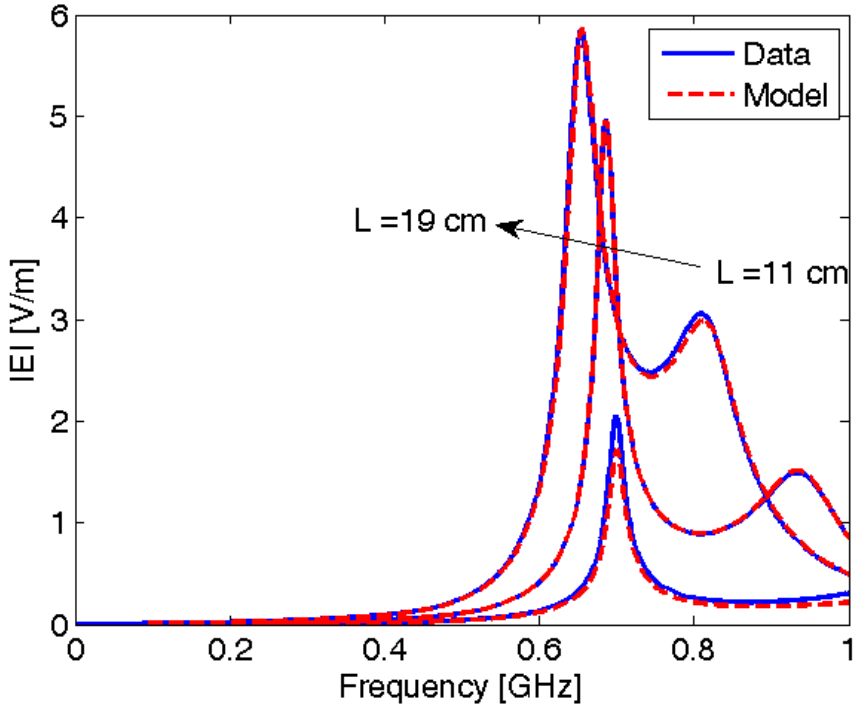

|E| [V/m]
8
6
4
2
0
20
15
10
Length [cm]
0
0.2
0.4
0.6
0.8
1
Frequency [GHz]

L=15 cm

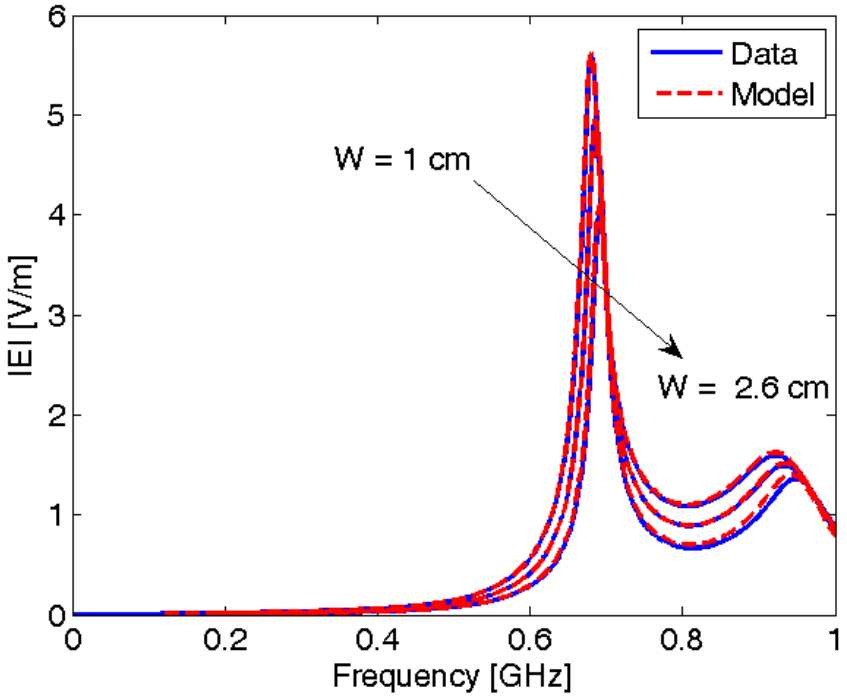

|E| [V/m]
6
4
2
0
2.5
2
1.5
1
Width [cm]
0
0.2
0.4
0.6
0.8
1
Frequency [GHz]



W=1.8 cm


Data
Model
L =19 cm
L =11 cm
|E| [V/m]
Frequency [GHz]
0
1
2
3
4
5
6
0.2
0.4
0.6
0.8

L=15 cm


Data
Model
W = 1 cm
W = 2.6 cm
|E| [V/m]
Frequency [GHz]
0
1
2
3
4
5
6
0.2
0.4
0.6
0.8

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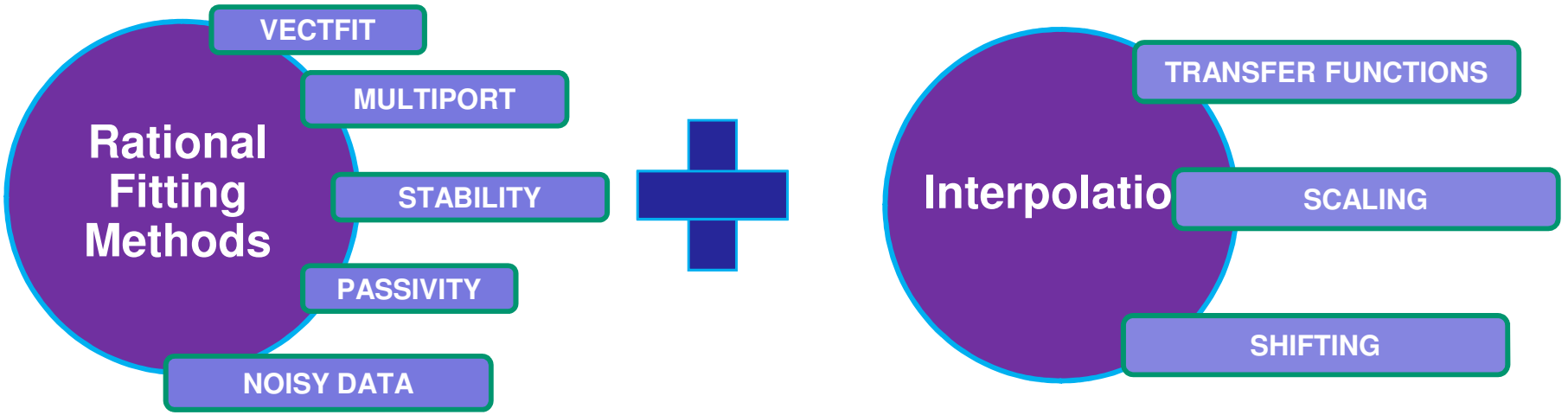
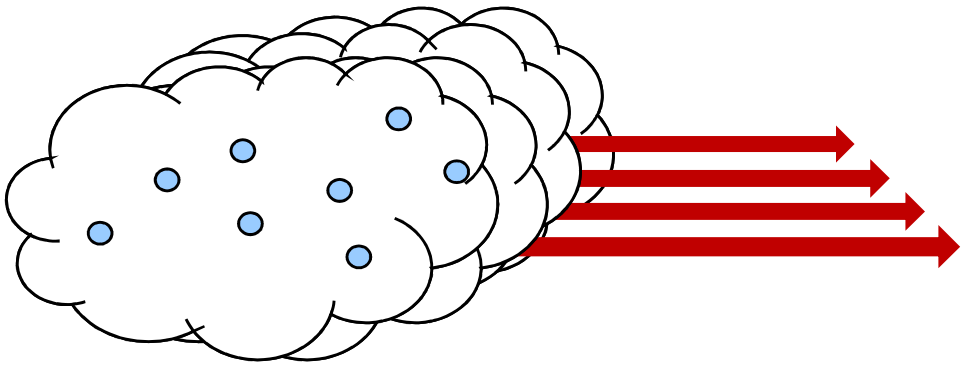


data-driven PMOR



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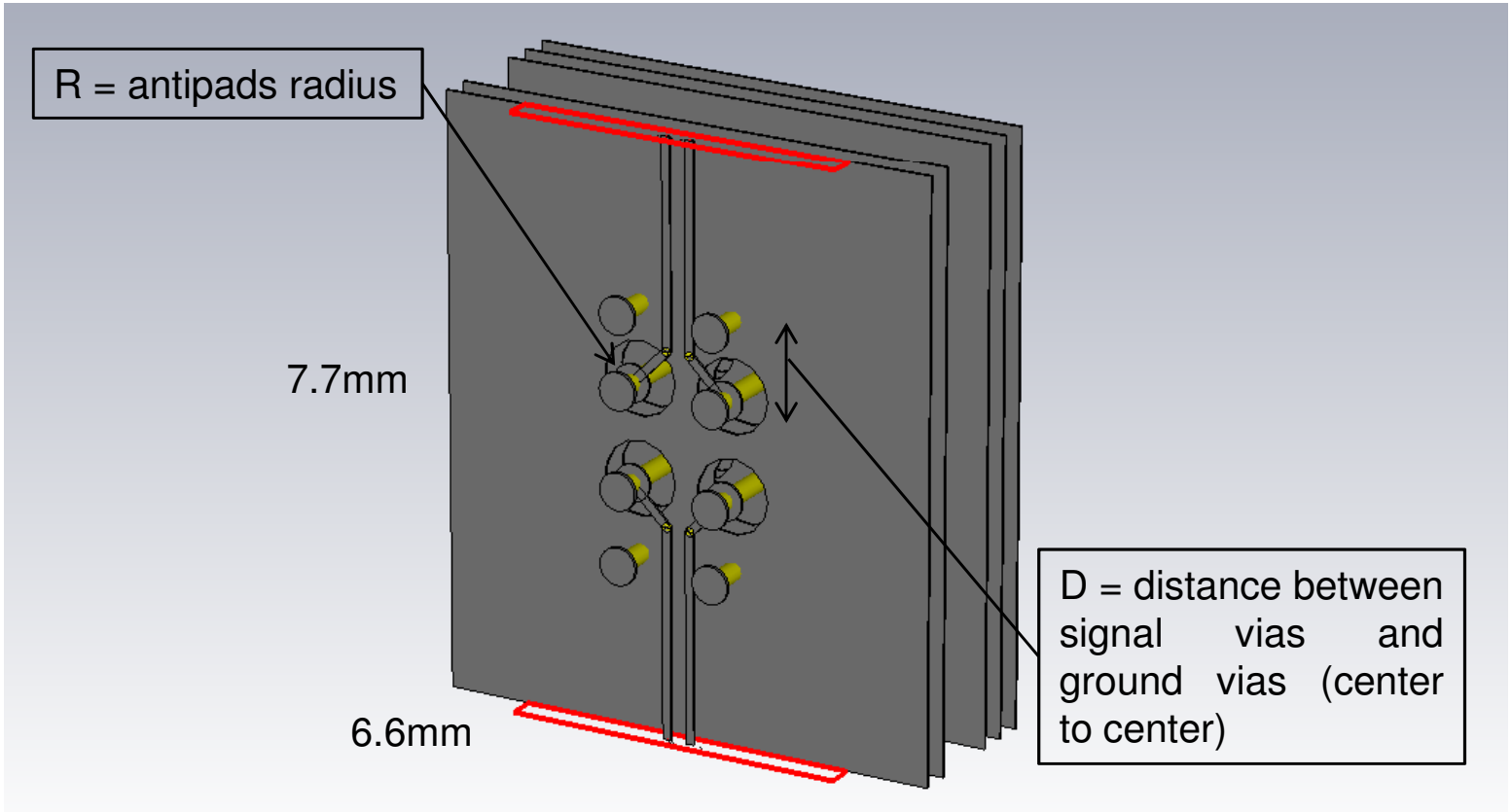
$$\mathbf{H}(s,\mathbf{g}) = \mathbf{C}(\mathbf{g})(s\mathbf{I} - \mathbf{A}(\mathbf{g}))^{-1}\mathbf{B}(\mathbf{g}) + \mathbf{D}(\mathbf{g})$$

scattered data

3D example: PCB

Parameter	Min	Max
Frequency (freq)	0 Hz	20 GHz
Antipads radius (R)	0.4826 mm	0.6026 mm
Distance (D)	1.2525 mm	2.4525 mm



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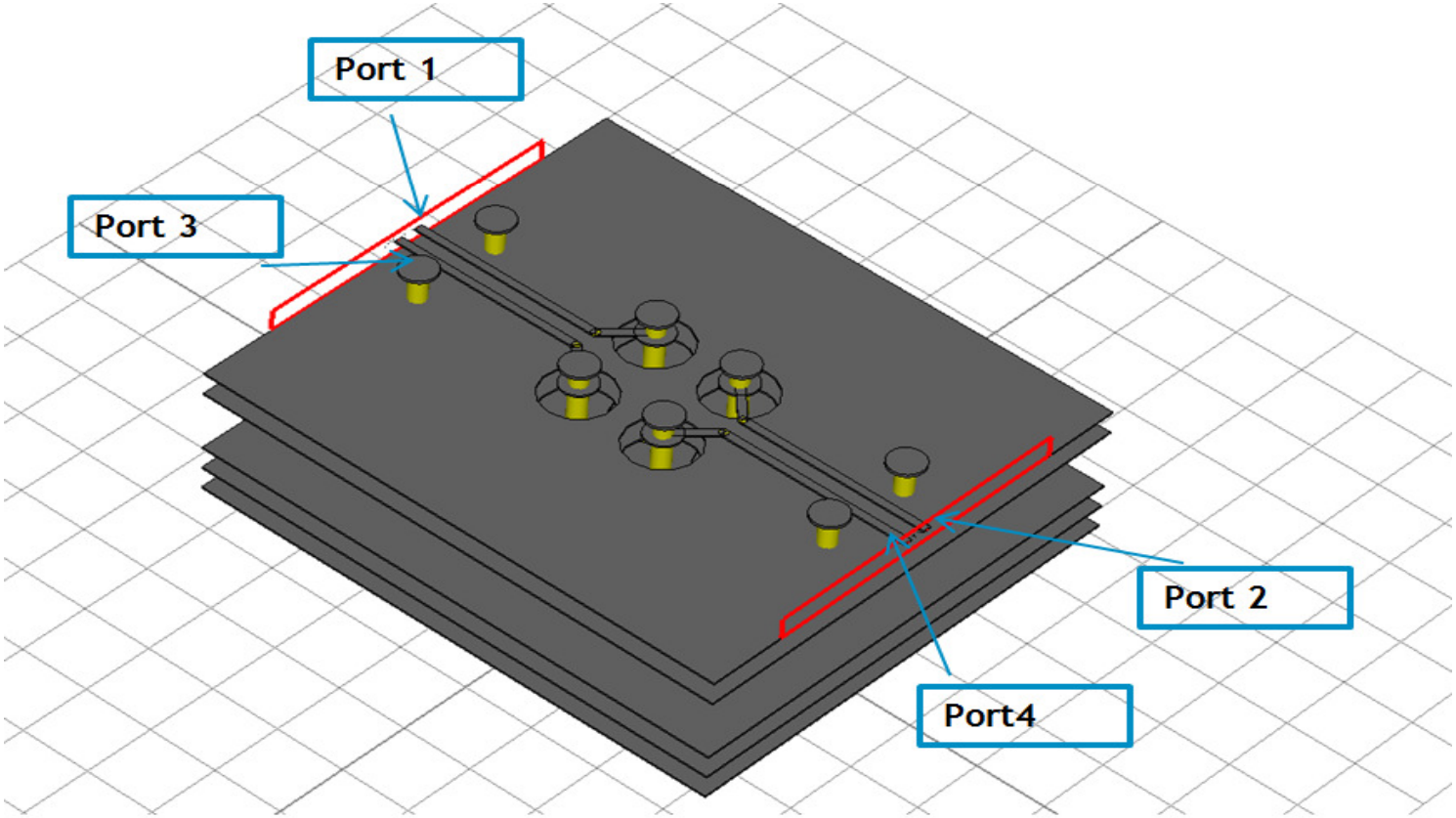
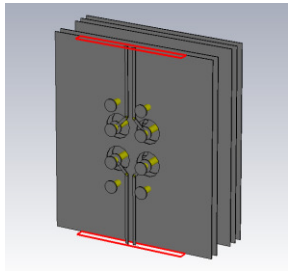
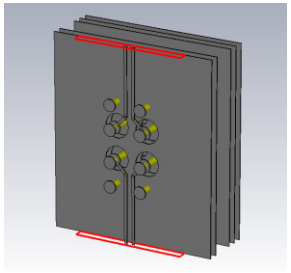




Step	CPU time
Estimation grid by solver (4 × 6) (R,D)	3 h 6 min
Validation grid by solver (3 × 5) (R,D)	1 h 56 min 15 s
Building model	5 min 49 s
Validating model	11 s
Evaluating solver (one frequency response)	7 min 45 s
Evaluating model (one frequency response)	0.1 s



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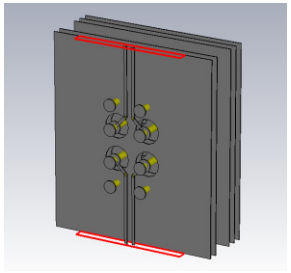
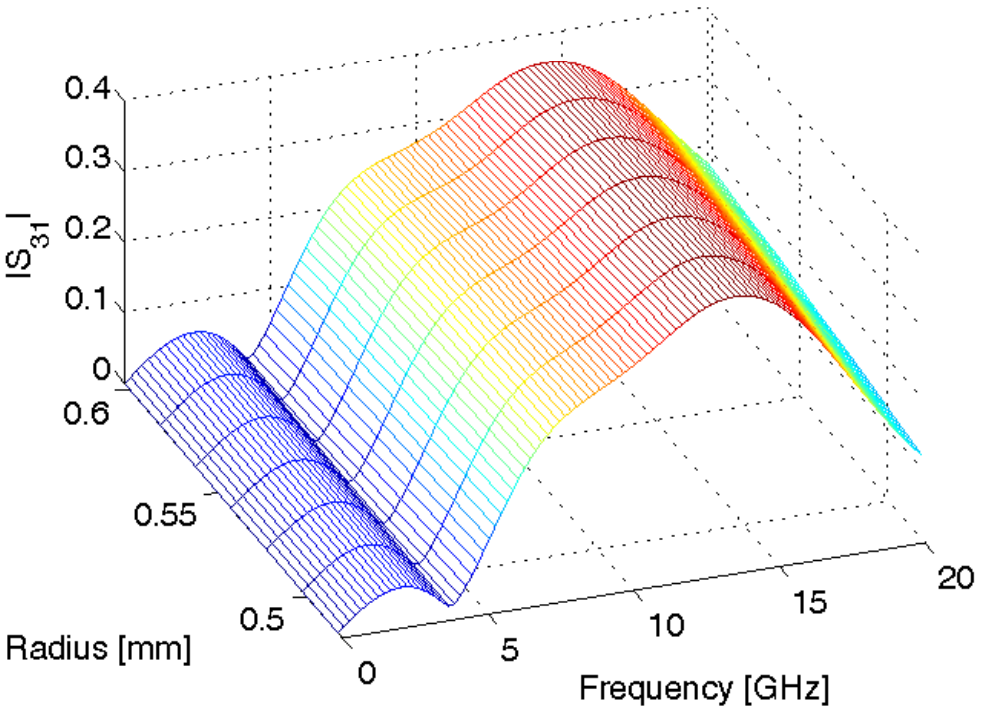
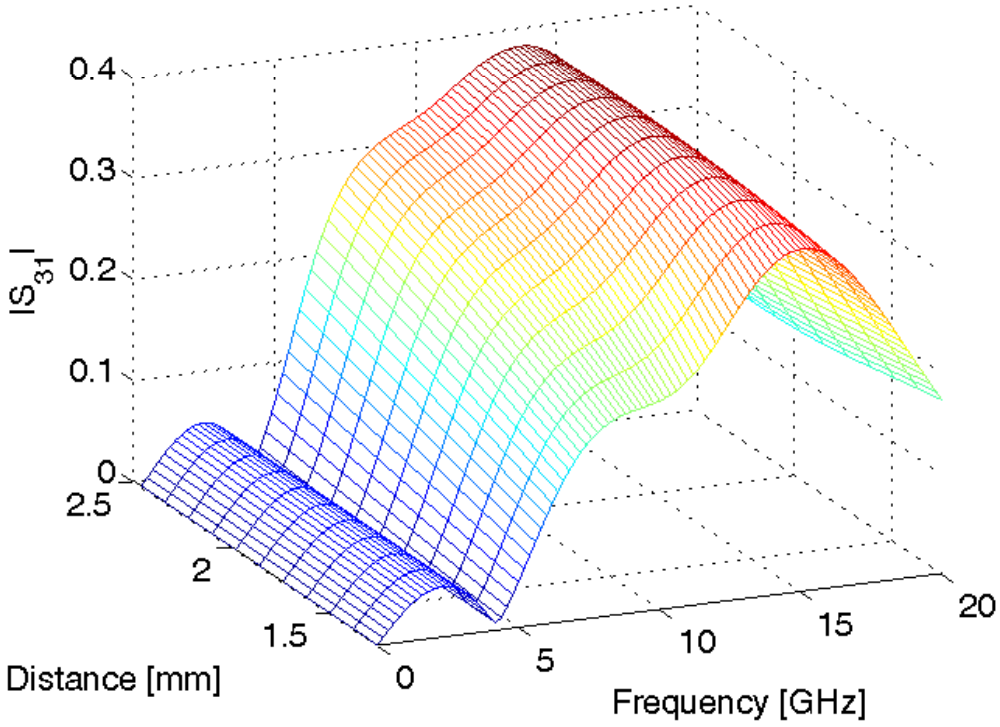
Speed-up 4650 x

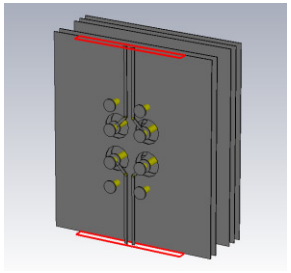


D=1.8525 mm



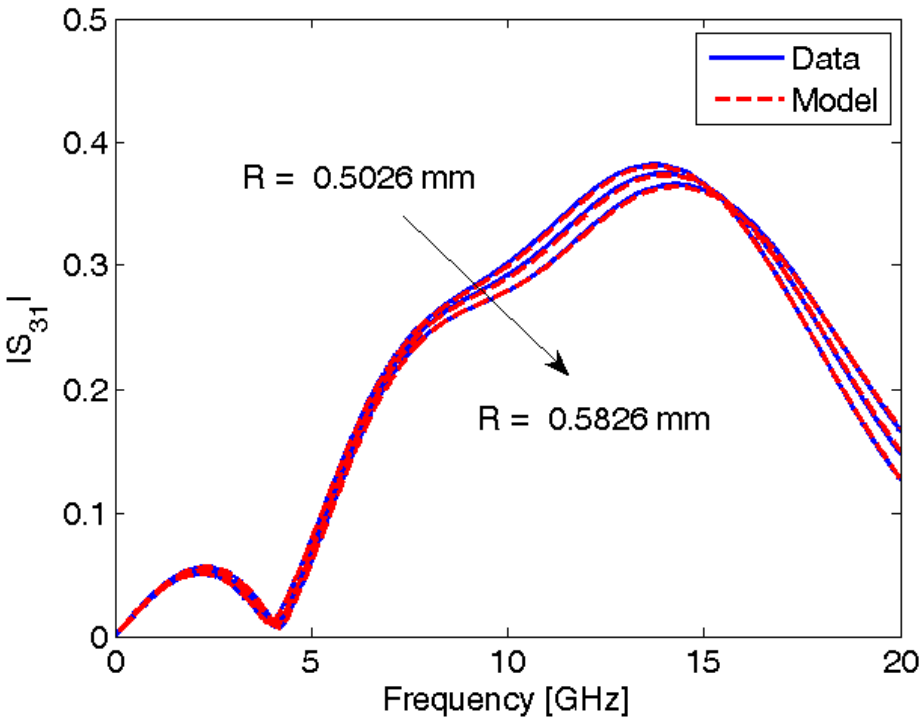
R=0.543 mm

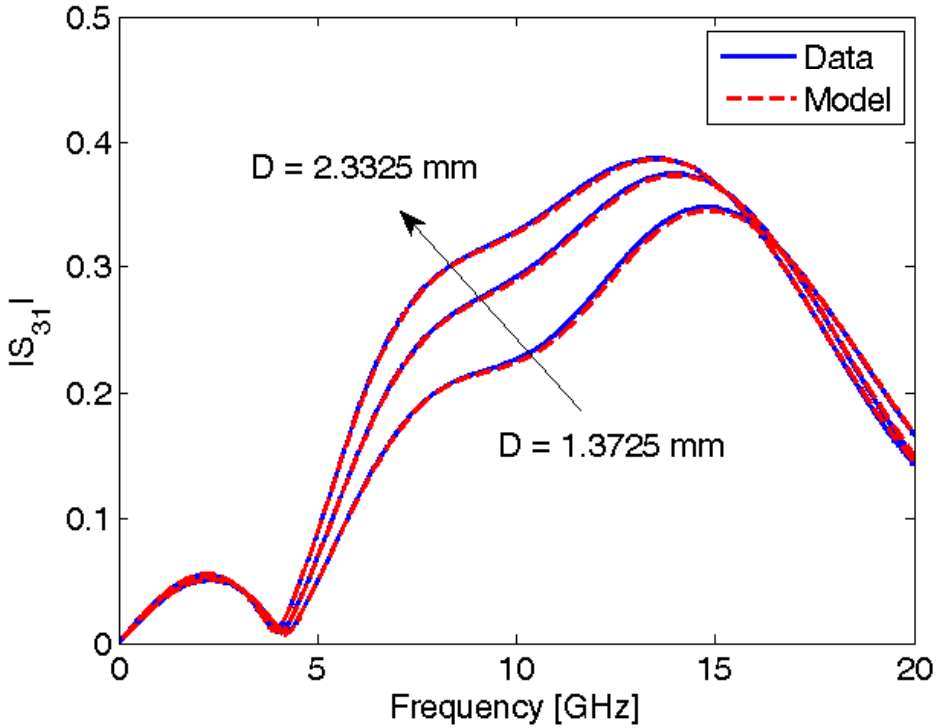


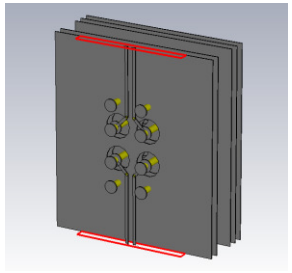


D=1.8525 mm

R=0.543 mm







D=1.8525 mm

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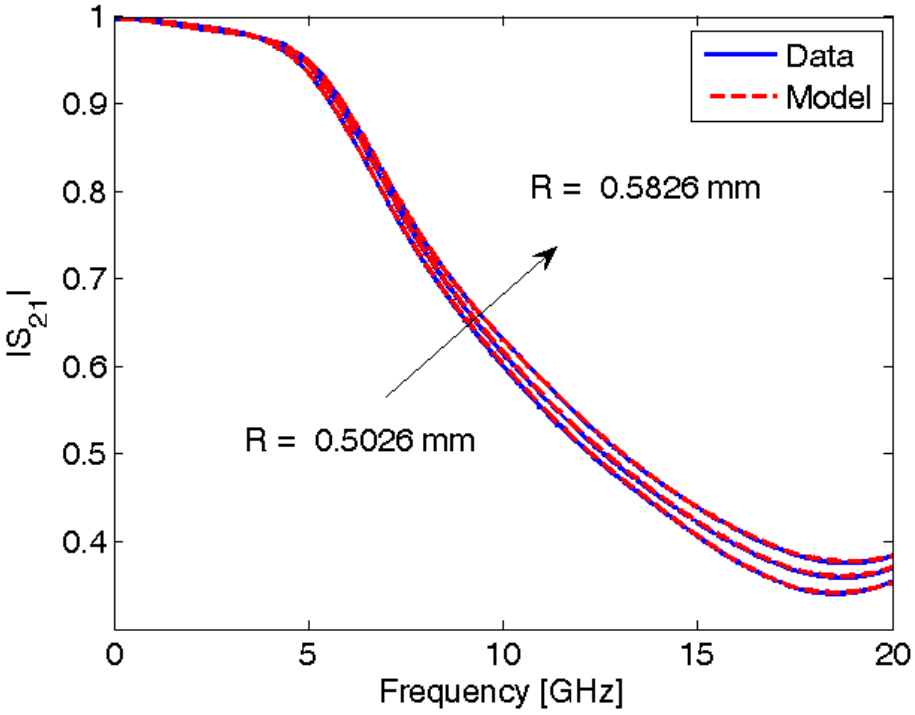

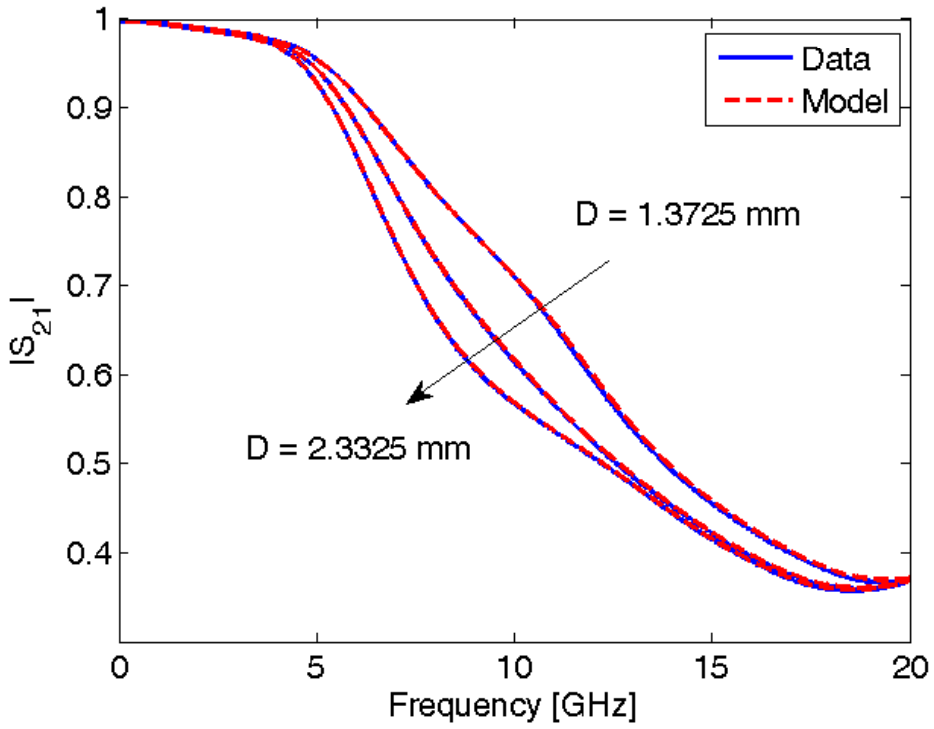

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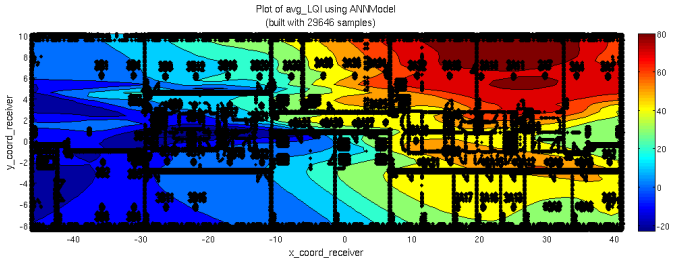
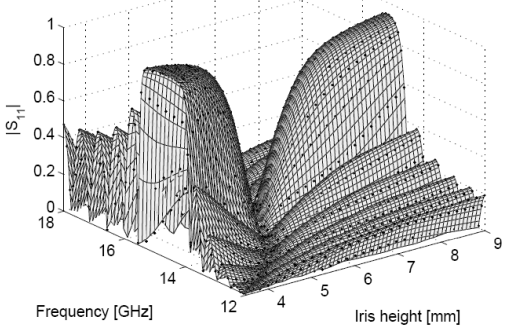
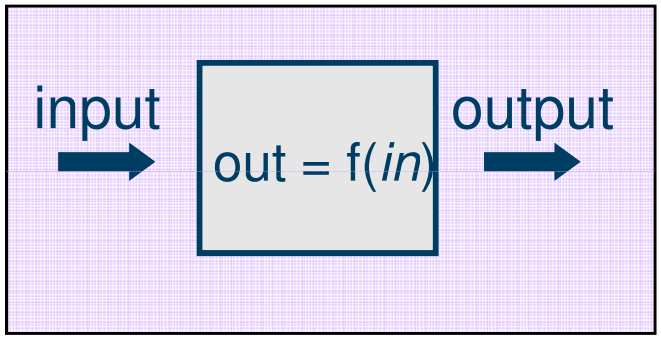
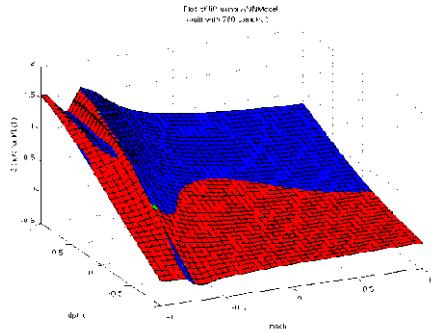


electronics

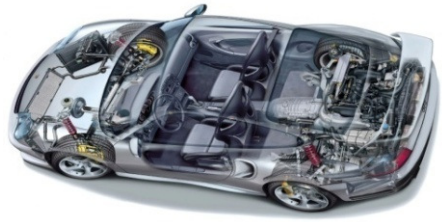




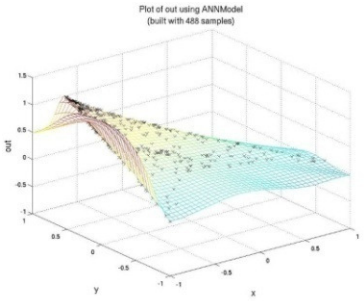
fluid dynamics



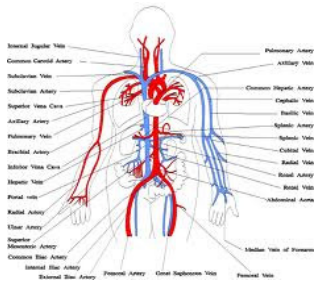
automotive



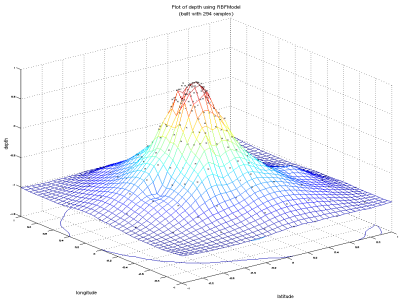
chemistry

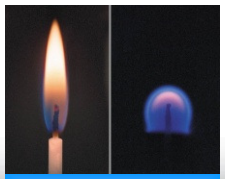
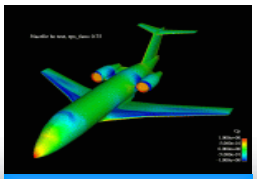
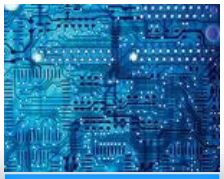


biomodeling



geology




Automotive | Chemistry | Aerodynamics | Electronics | Metallurgy

Design variables

width, temperature, angle, frequency, ...

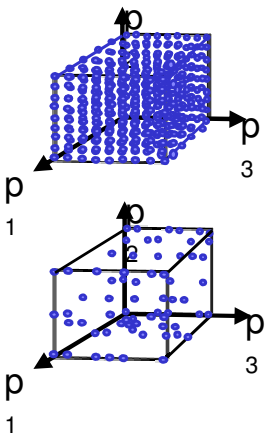
Simulation Model

Fluent®, HSPICE®, CST®, Comsol®, Abaqus®, ...

Costly

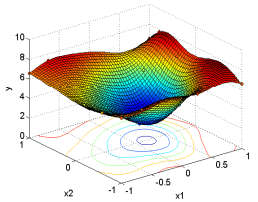
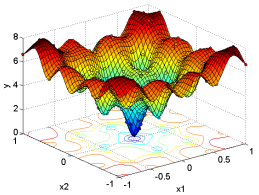
Response variables

lift, S-parameters, pressure, stress, ...



Configurable infrastructure

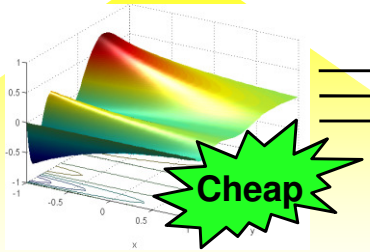
Adaptive Modeling

Distributed Computing

Design variables

Response variables

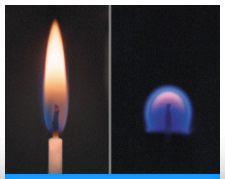
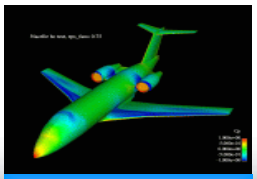
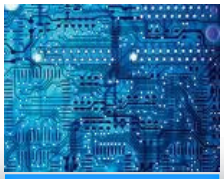


Cheap

Parameterized Macromodel

Neural network, Kriging, SVM, rational function, spline,...

Prototyping | Optimization | Sensitivity Analysis | CAD/CAM/CAE Environment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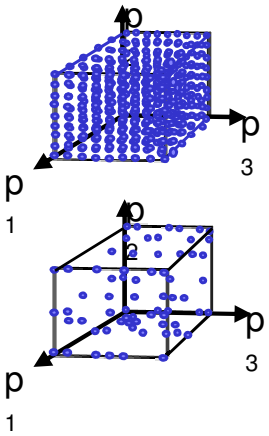
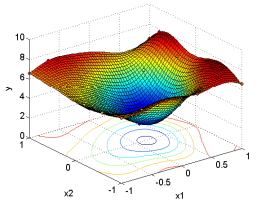
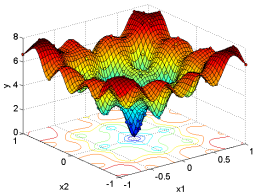


Configurable infrastructure

Adaptive Modeling

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Design variables

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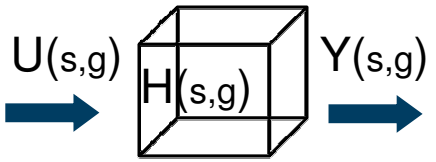
Parameterized macromodels

Multiple design variables



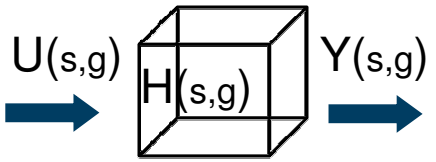
parameterized macromodel

Compact models

Efficient design activities (excellent speed-ups)

- **Multiple simulations (measurements)**
  - **Design space optimization, exploration, sensitivity analysis**

Parameterized macromodels



parameterized macromodel

Time-domain simulations

- **Non-linear drivers and receivers**

Stochastic modeling

- **impact of manufacturing tolerances**

Models from measurements

- **noise to handle**

Applications in different domains

Questions

Contact info: francesco.ferranti@ugent.be

Recent publications

F. Ferranti, L. Knockaert, T. Dhaene, "Passivity-Preserving Parametric Macromodeling by Means of Scaled and Shifted State-Space Systems", IEEE Trans. on Microwave Theory and Techniques, vol. 59, no. 10, pp.2394-2403, October 2011.

F. Ferranti, T. Dhaene, L. Knockaert, G. Antonini and A. Ciccomancini Scogna, "Scalable Compact Models for Fast Design Optimization of Complex Electromagnetic Systems", International Journal of RF and Microwave Computer-Aided Engineering, vol. 22, no. 1, pp. 20-29, January 2012.

F. Ferranti, M. Nakhla, G. Antonini, T. Dhaene, L. Knockaert, A. E. Ruehli, “Interpolation-based Parameterized Model Order Reduction of Delayed Systems”, IEEE Trans. on Microwave Theory and Techniques, vol. 60, no. 3, pp. 431-440, March 2012.

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